Essays on banking

Mosk, T.C.

Publication date:
2014

Document Version
Publisher's PDF, also known as Version of record

Essays on Banking

Essays on Banking

Proefschrift ter verkrijging van de graad van doctor aan Tilburg University op gezag van de rector magnificus, prof. dr. Ph. Eijlander, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de aula van de Universiteit

op woensdag 23 april 2014 om 16.15 uur

door

Thomas Cornelis Mosk
geboren op 25 november 1983 te Wageningen.

Promotores:

Prof. Dr. Hans Degryse

Prof. Dr. Steven Ongena

Overige leden van de Promotiecommissie:

Prof. Dr. Thorsten Beck

Prof. Dr. Vasso Ioannidou

Prof. Dr. Michael Koetter

Prof. Dr. Mitchell Petersen

Acknowledgements

I met my supervisors Hans and Steven in 2008 at a conference in Soestduinen and at the annual research conference of the Dutch Central Bank, which made me decide to apply for a Ph.D. at Tilburg University. A decision I never regretted. They were terrific. I greatly appreciated Hans' patience and diligence. Even though I kept on giving many different exotic names to the same variable (*Maximum Exposure* in Chapter 3), he kept on reading my papers and sending his comments, even within one day. Steven is a data connoisseur and taught me to discover the gems and the limits of my datasets. He also has a great sense of language and helped to simplify and unify the different layers in my papers. Both Hans and Steven are warm personalities which never made me feel alone in my Ph.D. journey. Even their most critical comment always contained a smiley.

Jose has been very important for me. He invited me to become a visitor and "friend" of DePaul University, which eventually resulted in a very special friendship. My inbox is filled with literally hundreds of emails from Jose with subjects ranging from "File Delivered: CB Data Jose", "11AM would be better for me...", "where is the revenue data?" to "Candy seat" and "Happy Birthday!". His advice was thoughtful and rigorous. I loved our dinners in the Blue Bird in Chicago and Festina Lente in Amsterdam and I hope many will follow.

I met my committee members Thorsten, Vasso, Mitchell and Michael at different points during my Ph.D. studies. Thorsten was the chairman of the European Banking Center and enabled me as Ph.D. student to attend interesting banking conferences and seminars. At these seminars Vasso always made sharp comments which impressed me. During my visit at Northwestern I had very cool and thoughtful conversations with Mitchell about my job market paper (Chapter 2) and he taught me the secrets of the academic elevator pitch. Michael was at the University of Groningen were I did my undergraduate studies, but we really met during the academic job market in Frankfurt. It was a natural choice to ask them to become part of my dissertation committee and their numerous comments improved my papers a lot.

Although I was most of the time in Amsterdam, at the days I was in room K 914 in Tilburg, I bombarded my colleagues with questions. Martijn, Francisco, Vincent, Patrick and Anton, thank you for listening, reading my work and giving advice. The Finance Department at Tilburg University provided me an ambitious but very supportive environment to obtain my Ph.D. I was privileged to have financial support, seminar preparation lunches, research communication games and job market mock interviews. Thank you Marco, Lieven, Frank, Fabio, Fabio, Alberto, Olivier, Joost, Maria Fabiana, Luc, Rik, Juan Carlos, Peter, Jos, Oliver and Bas.

How could I have learned to write about banks without being in a real bank? I am very grateful to the bank for allowing me to use its data and for its hospitality during my visits. The discussions with the Head Corporate and Markets Risk, his business manager, and many other people were challenging and gave me many ideas for my dissertation. I will not forget the day that a software programmer explained me that the "O" and the "G" in my data stand for 'Offered' and 'Accepted' interest rate. This conversation resulted in my job market paper 'Bargaining with a Bank' (Chapter 2).

During my Ph.D. I met the Dutch artist Daniel Rozenberg (Dadara). Dadara is the first artist who founded his own bank – the Exchanghibition Bank. He involved me in his project and I traveled as Exchanghibition Banker, together with Daan, Ali, Egbert, Jasha, Jasper, Elya, Roderik and Joris, to Portugal, Berlin and the Burning Man Festival in the U.S. Dadara's 'Transformoney Tree' installation at the Burning Man Festival allowed visitors to paint and draw on dollar bills and replace the financial value for their personal values. Participants contributed to the installation by gluing their customized dollar bills to the Transformoney Tree and received in exchange a bank note of the Exchanghibition Bank. The combination of doing research on banks and at the same time being involved in an art project on banks was very special.

Finally, I would like to thank my family and friends, in particular my parents, Benjamin, Roel, Jurriën, Willem, Maik, Dilip, Rutger, Marcel, Sander, Robert, Marieke, Liset, and Genna. It was great to have them with me.

Thomas Mosk

Frankfurt, 2014

The Transformoney Tree

The Transformoney Tree at the 2012 Burning Man Festival in the Black Rock Desert in Nevada (U.S.). From left to right the Exchanghibition Bankers Egbert-Jan Weber, Dadara (CEO), Joris Hofmans and Thomas Mosk. Photo by Eric Bouvet – appeared in Paris Match.

Contents

Introduction

An important role of banks is to screen and monitor borrowers on behalf of their depositors (Diamond, 1984). It would be very costly if every depositor, like you and me, has to review 10 credit applications on a weekly basis. Banks specialize in extracting and processing information concerning borrowers through their close relationship with them and in a way that is not replicable by individual depositors. Therefore, one of the main tasks of a bank is to collect and process information.

Banks collect and process information in various ways. For example, a bank could only use the financial records of a firm to make a lending decision. This quantitative numerical information is often labeled as ‘hard information’. In contrast, a bank could talk with the entrepreneur to collect so called ‘soft information’ about the firm, such as a judgment about the managerial qualities of the entrepreneur. The way how banks collect and process information is important, because it affects the lending decisions of the bank and the terms of the credit contract.

This dissertation studies how banks collect and process information. The first chapter studies how the organizational structure of a bank affects the processing of information. The second chapter studies how a bank uses information collected over the lending relationship in credit negotiations. The last chapter is joint work with Hans Degryse, Jose Liberti and Steven Ongena and studies how a bank uses ‘soft information’ to monitor small firms. To answer these questions this dissertation uses hand collected internal bank data. The internal bank data opens the black box how banks communicate internally, negotiate and monitor small firms.

The first chapter investigates whether the organizational structure of a bank affects the incentives of loan officers to manipulate information. Banks have different organizational structures. There are very large banks, such as HSBC, Deutsche Bank and ING Bank, and very small community banks with just a few branches. Economic theory predicts that the structure of an organization affects the way how people communicate. One specific prediction is that the delegation of decision making authority reduces incentives to manipulate information (Dessein, 2002). To test this prediction, Chapter 1 exploits an organizational change in a large commercial bank. Loan officers could manipulate information by using multiple scoring trials to change information to make the credit application look better. The chapter firstly shows that loan officers manipulate information to increase the likelihood of a credit approval and are more likely to manipulate information of credit applications with a large new credit volume and non-lending product sales, which reflects the structure of their compensation. Subsequently, the chapter shows that the delegation of decision making authority to their superior decreases their incentives to manipulate information. Their superior has a similar compensation structure and is more likely to approve credit applications with non-lending product sales, which shows that the delegation of decision making authority is associated with a loss of control.

Banks could use the private information which they collect over the lending relationship in credit negotiations. For example, a bank could charge a successful firm the average market interest rate, which also other banks charge, even though the bank knows that the prospects of the firm are better than average. As a result, the bank makes profit because the bank has better information about the firm than other banks which do not lend to the firm. According to this intuition, the information collected over the lending relationship could give banks bargaining power in credit negotiations (Rajan, 1992).

Chapter 2 studies how a large commercial bank negotiates with small firms and is the first empirical study on the bargaining process in the credit market. The chapter shows that in a typical credit negotiation the firm and the bank firstly sets the collateral requirements, then the non-interest credit terms of the credit lines and term loans and finally the interest rates and fees. Subsequently, the chapter shows that bank extracts rents in the first offer from relationships and opaque firms and these firms are less likely to negotiate interest rate concessions, which suggests that informational frictions in the credit market give banks bargaining power. Finally, the chapter shows that negotiating pays off. Negotiating firms pay a 33 basis points lower interest rate than otherwise similar firms which accept the first offer.

Chapter 3 studies how a bank uses ‘soft information' in lending decisions. We show that the collection of ‘soft information’ and the exercising of loan officer discretion helps to monitor firms. We measure loan officer discretion as the deviations in granted loan amounts from the amounts stemming from the bank's own credit scoring model. Soft information guides discretion, and helps in predicting loan default even when controlling for all available public and private information. Loan officers use soft information when deciding on the loan amount that is being granted: A one standard deviation of more favourable 'soft information' results in the granting of a 16 percent higher loan amount. Beyond using soft information, loan officer discretion per se neither improves nor deteriorates loan outcomes.

The main contribution of the dissertation to the literature is twofold. First, the first chapter shows that the organizational structure of a bank affects the incentives of loan officers to manipulate information. Second, chapter 2 and 3 show that the private information which banks collect over the banking relationship affects the bargaining behaviour in credit negotiations and discretionary lending decisions of loan officers, as relationship lending theories argue (Sharpe, 1990; Rajan, 1992).

I Delegation of Authority and Information Manipulation: Evidence from Bank Lending Decisions

Abstract

This paper exploits an organizational change in a large commercial bank to investigate how delegation of authority affects loan officers' incentives to manipulate information. Loan officers manipulate information to increase the likelihood of a credit approval and are more likely to manipulate information of credit applications with a large new credit volume and non-lending product sales, which reflects the structure of their compensation. The delegation of approval authority to their superior decreases their incentives to manipulate information. However, their superior has a similar compensation structure and is more likely to approve credit applications with non-lending product sales, which shows that the delegation of authority is associated with a loss of control.

1. Introduction

The task of collecting information and decision making is often separated in large organizations. For example, in a bank, loan officers collect information about credit applicants, while their superiors often make the credit approval decisions. Agents can strategically communicate their private information by changing or withholding some of their information to affect the outcomes of the decision making process. Agents will manipulate their information if their objectives are not perfectly aligned with those of the principal (Crawford and Sobel, 1982). The delegation of authority fosters communication compared to the case where the principle is in charge, but results simultaneously in a loss of control (Dessein, 2002; Harris and Raviv, 2005; Marino and Matsusaka, 2005).

This paper exploits an organizational change in a large commercial bank to investigate how delegation of authority affects loan officers' incentives to manipulate information. The paper finds that the delegation of authority to the superior of the loan officer decreases their incentives to manipulate information. However, their superior is more likely to approve credit applications with non-lending products sales than an approval decision made before the delegation of authority, which shows that the delegation of authority is associated with a loss of control.

Small business lending is well suited for an inquiry into the effect of organizational structure on information manipulation. First, the task of collecting information about credit applicants and the approval of credit applications is often separated in commercial banks. In addition, the objectives of loan officers and the approval authority might differ due to the remuneration structure and soft, non-verifiable information is important in small business lending (Berger, Miller, Petersen, Rajan, and Stein, 2005). These three ingredients enable agents to strategically transmit information (Crawford and Sobel, 1982). Second, commercial banks use advanced risk management software which records the information used in credit decisions. [1] This allows to study the loan approval process and the exchange of information between the loan officer and the approval authority, while in other industries the exchange of information remains unrecorded.

To test the impact of the delegation of authority on information manipulation this paper exploits an organizational change in the approval process of small business loans in a large commercial bank in the Netherlands. In October 2010, the bank changed its approval process and delegated the authority to approve small business loans from risk management to local business directors. The main difference between a risk manager and a business director is that the lending volume and non-lending product sales affect the remuneration of the local business director, but not the remuneration of a risk manager. Loan officers have a similar compensation package as the business director. Their objectives are therefore more similar to the objectives of the business director than the objectives of the risk manager. The bank delegated the authority to approve credit applications to the business directors of the branches, except for a group of branches which is used as control group.[2]

The data employed in this paper contain more than 23,000 credit applications over the period January 2009 to March 2011 and include information about the exchange of information between the loan officer and the approval authority. This paper uses the approach of Berg, Puri and Rocholl (2013) to measure information manipulation. They show that loan officers use multiple scoring trials to adjust the input parameters of the risk management software to improve the approval score of the credit applications if the first trial is below an automatic approval cut-off. The bank in this paper uses similar risk management software and the paper uses the number of scoring trials as information manipulation measure. This paper shows empirically that loan officers are more likely to

[1] Liberti and Mian (2009) and Agarwal and Hauswald (2010) provide examples of the hierarchical approval process in two US banks. Agarwal and Hauswald (2010) and Berg, Puri and Rocholl (2013) describe the use of risk management software in a U.S. and German bank.

[2] The branches in the control group were part of a mandatory divestment. The European Commission forced the bank to sell some of their branches to a competing bank. During the transition period these branches operated independently and were not subject to the organizational change. In all other aspects the divested branches are similar to the other branches of the bank.

use multiple trials if the applying firm purchases non-lending products and the credit volume of application is large, which suggests that the loan officers use scoring trials to manipulate information.[3]

Using a difference-in-difference methodology this paper tests the hypothesis of Dessein (2002) that the delegation of authority reduces incentives to manipulate information. The paper finds that loan officers use fewer scoring trials if their business director makes the approval decision instead of a risk manager. In addition, the paper shows that the likelihood of an improvement of the approval score between the first and the final trial decreases if the business director approves the credit applications. The delegation of authority only affects the loan officers' incentives to manipulate information if the objectives of their business director are more similar to their objectives than the objectives of the risk manager. To test this prediction the paper examines whether business directors make different approval decisions than risk managers if they face a similar credit application. The results show that business directors make a different credit decision than risk managers if a firm purchases non-lending products. This suggests that the objectives of the business director are similar to the objectives of the loan officers.

The main contribution of this paper is to provide novel evidence on information manipulation and the effects of organizational design on the agent's incentives to manipulate information. The paper is related to the organizational economics literature examining the effect of organizational structure on the use of information and decision making.[4] Studies by Liberti, (2005), Agarwal and Hauswald (2010), and Qian, Strahan and Yang (2012) find that the delegation of authority and greater autonomy improves the incentives of loan officers to exert effort and collect soft information. In contrast, this

[3] The paper also shows that loan officers use more scoring trials if the first approval score indicates a low probability of approval and that loan officers are more likely to improve the approval score over the scoring trials than downgrading the score. Both findings provide additional evidence of information manipulation and are in line with the findings of Berg, Puri and Rocholl (2013). The current version of the data does not include loan performance data which would enable to test whether multiple trials predict default.

[4] In contrast, Liberti, Seru, and Vig (2012) study the impact of a change in the informational environment (an expansion of the credit registry) on the organizational structure of a large bank.

study focuses on the effects of delegation on information manipulation.[5] Liberti and Mian (2009) show that a greater hierarchical and geographical distance leads to less reliance on soft information, but do not test whether this effect is due to the problem of information manipulation.

This paper uses a direct measure of information manipulation using the approach of Berg, Puri and Rocholl (2013). An important difference is that this study examines the effect of the delegation of authority on information manipulation and therefore directly tests the prediction of Dessein (2002). In addition, the loan officers in Berg, Puri and Rocholl (2013) only manipulate information in the bank's risk management software, while in this paper information manipulation affects real decision making. This paper shows that the delegation of authority could reduce communication problems. Related, Hertzberg, Liberti and Paravisini (2010) show that a loan officer rotation policy could mitigate agency problems in communication.

The rest of the paper is organized as follows. Section 2 describes the approval process and the organizational change. Section 3 describes the sample, the information manipulation measures and presents the descriptive statistics. Section 4 examines the determinants of information manipulation and section 5 investigates the effect of the delegation of authority on information manipulation. Section 6 investigates the effect of the delegation of authority on the approval decision and section 7 concludes.

[5] Berger, Miller, Petersen, Rajan, and Stein (2005) find that large banks are less willing to provide credit to informationally opaque firms.

2. The credit application process and the organizational change

The data provider is one of the top five commercial banks in the Netherlands and its business practices, information acquisition and loan data are highly representative for the banking industry. The business banking division of the bank provides credit lines, term loans and non-lending products to small and medium enterprises. This division consists of over hundred business branches, covering all provinces in the Netherlands. A branch has one business director and a team of 10 to 20 loan officers. The business director is in charge of general business development and monitors, coordinates and helps the loan officers in their work. The loan officers meet prospective clients, handle credit applications and are in charge of developing the firm-bank relationship. The bank has also 4 regional risk management offices with 15 to 20 risk managers. The responsibility of risk mangers is to approve the credit applications in their region.

The structure of the compensation package of the loan officer is similar to the compensation package of the business director. The remuneration of the loan officers and the business directors consists of a fixed salary and performance based remuneration based on the risk weighted interest income and the non-interest income generated by their portfolio. The performance based remunerations is about 5 to 10 percent of the total fixed salary. In contrast, the performance based remuneration of the risk managers is based on the number of decisions they make, independent of the outcome of the decision. The difference in the remuneration packages of the loan officers and risk managers gives rise to a bias in the objective of the loan officer and the risk manager, which is one of the main assumptions of the communication models of Crawford and Sobel, (1982), Dessein (2002), Harris and Raviv (2005) and Marino and Matsusaka (2005).

2.1 The approval process

The approval process proceeds in the following way. First, the firm meets with a loan officer and discusses its business, credit demand and collateral. The firm provides information such as recent annual reports, forecasts and taxation reports. The loan officer enters all the firm data into the bank's risk management software and specifies the structure, maturity, collateralization, and the interest rate of the credit application. The loan officer could only proceed to the next step, the scoring of the application, once the credit application is complete.

Second, the loan officer ‘scores’ the credit application. The bank uses a credit scoring technology and an algorithm which determines whether an application needs an approval.[6] The algorithm, whose decision parameters are set by the headquarters, determines the *approval score*, which could be green, orange or red.[7] The main decision parameters of the algorithm include the firm’s credit rating, the collateral ratio and a credit policy score based on over 40 credit policy questions about the credit application.[8] The approval score allocates the approval authority of the credit application. Credit applications with a green approval score are automatically approved by the system. Credit applications with an orange and red approval score require an approval from risk management.[9] After the scoring a colleague of the loan officer checks the correctness of the hard information in the credit application and a senior loan officer or the business director gives permission to submit the credit application for approval.

Third, the risk manager evaluates the credit application with a red or orange approval score and ultimately decides whether to approve or reject the credit application. The risk manager uses the information about the firm, the credit application and additional notes of the loan officer in the risk management software to make its decision and has no direct contact with the firm. Therefore, its decision relies completely on the information provided by the loan officer. Although the bank checks the correctness of the hard information in the credit application there are many fields in the credit application which are not verifiable. For example, the loan officer has to give a written motivation for

---

[6] Credit scoring technologies are widely applied in small business lending in the U.S. and Europe (Akhavein, Frame, and White, 2005).

[7] This system is similar to the credit approval system described in Agarwal and Hauswald (2010) and Berg, Puri and Rocholl (2013). Specialized firms, such as TCI Loan origination solutions, Lenders Logic and Global Wave Banking Solutions offer similar specialized software packages to commercial banks for loan origination, workflow, approval and monitoring of commercial loans.

[8] The firm’s credit rating is based on more than 20 parameters. The credit policy questions include questions about the financial position and reputation of the owner, the nature of the credit demand and the quality of the collateral.

[9] A risk manager in a regional approval office makes the approval decision for credit applications with an orange score and a senior risk manager makes the approval decisions for credit applications with a red score.

the credit applications. After the approval of the credit application, the loan officer could prepare the credit offer and send the offer to the firm.

2.2 The organizational change

In October 2010, the bank changed its approval process and delegated the authority to approve credit applications from risk management to the business directors of the branches. The bank delegated authority because of the implementation of the “three lines of defense” risk management strategy. An essential element of this strategy is that the business instead of the back office (e.g. risk management) becomes responsible for risk taking.[10] The “three lines of defense” risk management strategy was implemented bank wide and was not specific to the small business lending division or driven by the performance of this division. In addition, the implementation of this strategy was also not specifically implemented by this bank. Several large banks implemented this strategy and large auditing firms offered consultancy services to implement this strategy. However, the implementation of is “three lines of defense” strategy was not forced by the regulator.[11] The paper discusses this organizational change in detail below. From this point forward, the original setting is referred to as *before the change* and the setting after the delegation of authority as *after the change.*

The delegation of the approval authority affected all branches, except for the branches which were part of a mandatory divestment, which the paper uses as control group. Figure 1 shows the timeline of the divestment of the branches and the delegation of authority. The European Commission forced the bank in 2007, before the crisis, to sell some of their branches to a competing bank. The bank selected the branches and the branches operated after the selection independently as a subsidiary of the bank. In 2008, the bank signed an agreement to sell the branches to another large European bank. The transfer of the shares took place in the beginning of 2010. After the official divestment

[10] In this model, the first line of defense is the business itself and the other two lines risk management and the internal and external audit. One key element of the risk management strategy is that the business takes full responsibility for the risks that arise in their operations. To give this responsibility, risk management delegated the authority to approve credit applications to local business directors.

[11] For example, Ernst and Young issued a white paper to advice banks how to implement the “Three Lines of Defense Strategy”.

the divested branches operated as independent subsidiary of the new owner and continued to use the same lending software, but were not subject to the organizational change. The empirical section compares in detail the treated and control branches before and after the change and uses the divestment date for a placebo test.

The remaining part of this section describes in detailed how the bank implemented the organizational change and how it affected the approval process. Figure 1 shows the organizational structure of the credit approval process of the treated and control branches before and after the organizational change.[12] Before the change risk managers approved credit applications with an orange or red approval score. The business directors gave the loan officer permission to submit the credit offer for approval, but did not make the final approval decision. After the change, the bank delegated the authority to approve credit applications with a green or orange approval score to the business directors of the treated branches. The organizational structure of the control branches did not change and risk managers continued to make the approval decision.

Both the treated and control branches continued to use the risk management software to approve credit applications. Business directors evaluate the credit application in a similar way as a risk manager and could only approve the credit application via the risk management system. The algorithm to determine the approval score did change over time and became stricter around the time of the change, but changes in the algorithm affected both the treated and control branches.

The remuneration package of the loan officers of the treated and control branches did not change after the organizational change. However, after the organizational change, the bank included a performance measure for the credit quality in the compensation package of the business directors of the treated branches. This change in the remuneration package of the business director is in line with the predictions of Dessein (2002). Dessein (2002) predicts that it is optimal for the principal to delegate authority to an intermediary if the principal *"could freely choose an intermediary's level of bias"* and the total bias of

[12] Liberti (2005) studies a similar hierarchical change. The bank in his study fully delegated authority to senior loan officers and partially delegated authority by redefining team roles. However, his study focuses on the effect of delegation on the incentives of loan officers to exert effort, while this paper focuses on the incentives of loan officers to strategically transmit information.

the agent is not very large. Therefore, the delegation of authority from risk management to the business directors reduces the bias in objectives between the information collecting agent (the loan officer) and the approval authority.

Risk managers make their credit approval decision based on the firm specific information collected by the loan officer and do not collect firm specific information themselves. Their firm specific information set is a subset of the information set of the loan officer. Business directors do not collect firm specific information either. However they do possibly know the firm or the owners.

3. Data

3.1 The sample

The sample consists of 23,013 credit applications of small firms over the period January 2009 to March 2011. A branch handles on average 130 new credit applications from small and medium sized firms a year. These credit applications are applications for new credit and do not include renewals or renegotiations of existing loans.

The firms applying for credit are small and medium sized firms, such as farms, wholesalers, construction firms, architect bureaus and medical practices. The firms have a mean total asset size of 635 thousand euro and a mean turnover of 978 thousand euro.[13] In 48 percent of the credit applications the firm has an existing lending relationship with the bank and in 44 percent of the credit applications the firm also purchases non-lending products, such as cash management, foreign exchange and insurance products.[14] The average new credit volume of a credit application is 191 thousand euro. The firms apply for new credit to finance working capital and to finance fixed assets, such as real estate, machines and other equipment. The collateral ratio of the credit applications is 78 percent and the pledged collateral consists of corporate real estate, inventories, account

[13] The firms are comparable with small U.S. firms covered by the 2003 National Survey of Small Business Finance (NSSBF). The median firm in the NSSBF survey has an asset size between 100 and 240 thousand dollar and employs five to nine employees (Mach and Wolken, 2006).

[14] The data contains no details about the number of non-lending products. Santikian (2010) shows that U.S. firms purchase on average 10 non-lending products. The firms in her sample, however, are significantly larger than the firms in this paper.

receivables and personal guarantees. An average credit application consists of one credit line and one term loan and has an average maturity of 6 years.

Table I compares the summary statistics of the treated and control branches for the full sample. The average firm size is slightly smaller for the treated branches, but the leverage and credit rating of the firms applying for credit is fairly similar. In both the treatment and control branches about 50 percent of the firms have an existing lending relationship and 30 percent of the firms have debt from other banks. The treated branches are more likely to sell non-lending products than the control branches.[15] The size of the new credit volume is similar, but the collateral ratio of the treated branches is lower and the maturity about 6 months longer. Overall, there are no large differences between the firms and the credit applications of the treated and control branches.

3.2 Measuring information manipulation

In the application process the loan officer uses the algorithm to ‘score’ a credit application and then chooses based on the outcome how to proceed. The loan officer could abort the credit application, submit the application for approval or change any of the input parameters and initiate a new scoring trial. This enables the loan officer to manipulate the information in order to affect the outcome of the algorithm. For example the outcome could change from ‘red’ to ‘orange’ after several trials. The risk management software of the bank records each trial, but loan officers are in general not aware that all scoring trials are recorded and also the bank’s risk management department has not used it so far.

The paper uses the methodology of Berg, Puri and Rocholl (2013) to measure information manipulation. They use data from a large German bank and measure the number of trials the loan officer uses to score consumer loan applications. They show that loan officers use significantly more trials around the automatic rejection cut-off in the bank’s algorithm. Multiple scoring trials for a single credit application can be due to loan

[15] The non-interest income from non-lending product sales is observable in a due diligence by any potential buyer. Therefore it is unlikely that the competing bank bought underperforming branches without knowing this. The empirical section uses branch fixed effects to control for unobservable differences across branches.

officers honestly correcting false information from a former trial (the information correction hypothesis) or loan officers manipulate the information they have about their customers in order to increase the likelihood of an approval of their application. To distinguish between these two interpretations Berg, Puri and Rocholl (2013) estimate the effect of multiple scoring trials on the default rate of consumer loans and show that additional trials positively predict default, suggesting that loan officers manipulate information around the cut-off.

The data of this paper includes the number of scoring trials of each credit application and the main input parameters and outcomes of each trial, which enables to measure the adjustments between the first and last trial. Table II shows that loan officers use on average 10 scoring trials per credit application. This is significantly higher than the average of 2 scoring trials reported in Berg, Puri and Rocholl (2013). A difference in the number of input parameters in the algorithm is a plausible explanation for this difference. The algorithm of the bank in Berg, Puri and Rocholl (2013) is designed for consumer loans and is based on 5 main input parameters while the algorithm of the bank in this paper is designed for small business lending and is based on over 30 parameters and more than 40 credit policy questions. This could reflect the difference in complexity in the information and contractual structure between consumer and small business lending.

During the scoring trials loan officers can change the parameters of the scoring model to improve the approval score. For 15 percent of all credit applications the final approval score is better than the first approval score, while only for 4 percent of the credit applications the final approval score is worse than the first approval score. The fact that the approval score improves more frequently than deteriorates can be seen as a first indication that loan officer manipulate information instead of honestly correcting false information from a former trial. Table II presents the descriptive statistics for each first approval score (green, orange, or red). The results show that loan officers make more scoring trials if the first approval score is red and more importantly, the approval score improves for 40 percent of these red scored applications. In contrast, a decrease in the approval score of a green scored application happens less frequently. Overall, the descriptive statistic suggests that loan officers use scoring trials to improve the approval score of the credit application. The next section investigates the determinants of the scoring trials and the improvements of the approval score.

4. Determinants of information manipulation

An important empirical prediction of Crawford and Sobel (1982) is that agents manipulate information if the objectives of the principal and the agent are less similar. The paper uses the differences in the compensation packages of the loan officer and the risk manager to create empirical proxies which capture the differences in objectives between the loan officer and the risk manager. An important difference between the compensation package of a loan officer and a risk manager is that loan officers have a volume-based compensation and are compensated for the generated non-interest income, while the compensation packages of risk managers do not include these incentives. Agarwal and Ben-David (2012) show that a change from a fixed salary to a volume-based compensation affects the loan officer's incentives and results in a higher approval rate, larger loan sizes and a higher default rate. Santikian (2012) shows that the sales of non-lending products are important in small business lending. Based on the structure of the compensation packages of the bank and the empirical evidence from other banks, the expectation is that loan officers are more likely to manipulate information if the credit application is likely to get rejected (has a bad first approval score), has a large new credit volume and has additional sales of non-lending products. The paper tests this prediction by estimating the following specification:

$$\text{Ln}(Number\ of\ trials_{ijkt}) = \alpha + \delta_2 X_{ijkt} + \gamma_j + \gamma_t + \varepsilon_{ijkt}, \qquad (1)$$

where the $\text{Ln}(Number\ of\ trials_{ijt})$ is the natural logarithm of the number of scoring trials of the credit application *i* at branch *j* by loan officer *k* at time *t*, and X_{ijt} is a matrix of explanatory variables, γ_j are branch fixed effects, γ_t are year-month fixed effects and ε_{ijt} is the error term. The matrix of explanatory variables includes the outcomes of the first scoring trial (orange and red), firm characteristics (firm size, leverage and profitability), credit application characteristics (the natural logarithm of the new credit volume, the collateral ratio and the maturity) and relationship characteristics (lending relationship, lending from other banks, non-lending products). Standard errors are clustered at the branch level. [16]

Table III presents the empirical results and shows in column (1) that the outcomes of the first scoring trial and the sales of non-lending products are important determinants of the number of scoring trials. The number of scoring trials increases 17 percent if the first approval score is orange and 25 percent if the first approval score is red. These results are similar to Berg, Puri and Rocholl (2013), who find that a score worse than the automatic rejection cut-off in the first scoring trial is associated with 48 percent more scoring trials. The interpretation of these findings is that loan officers try to improve the approval score if the first approval score indicates that there is a high likelihood of a rejection of the application. By adjusting the first approval score, the credit application looks better, which increases the likelihood of an approval.

The paper finds that loan officers use 35 percent more scoring trials if firms purchase non-lending products. Loan officers are remunerated based on the non-interest income returns of their portfolio and put therefore more value on an approval of an application with potential sales of non-lending products. This is in line with the findings of Santikian (2012) that non-lending profits are an important driver of the credit terms of small business loans.[17] In addition, the results show that loan officers use more scoring trials if the credit application has a larger new credit volume. An increase in the new credit volume from the median new credit volume of 50 thousand euro by one standard deviation (223 thousand euro) leads to an increase in the number of scoring trials by (

[16] An alternative way to estimate this specification is to use a negative binomial regression. The results of a negative binomial regression are similar to the results of the log-linear model presented in this section.
[17] An alternative explanation of Santikian's (2012) result is that non-lending products are important in lending decisions because they provide more information about the firm (Petersen and Rajan, 1994). However, additional information from non-lending products does not explain that loan officers use more scoring trials.

223/50)· 0.059 = 26 percent.[18] These results suggest that the incentives of the loan officer to sell more non-lending products and increase the size of its portfolio are positively correlated with the number of scoring trials. Loan officers use less scoring trials for existing lending relationships and more for firms with debt from other banks, but these factors only marginally affect the number of scoring trials.

Differences in loan officers' career concerns and experience (loan officers have the same compensation package) could give them different incentives to manipulate information. To test this hypothesis the paper includes loan officer fixed effect to the specification and reports the results in column (2). The R-squared increases from 13 percent to 27 percent, which suggests that unobserved loan officer characteristics are an important determinant of the number of scoring trials. The results also show that for the same loan officer the outcome of the first approval score, sales of non-lending products and credit applications with larger credit volumes with longer maturities are still an important determinant of the number of scoring trials.

Next, the paper estimates the likelihood of a better approval score using a probit model and reports the marginal effects in column (3). Since the paper only observes variation in the dependent variable if the first approval score is orange and red, the paper only includes a dummy which equals one if the first approval score is orange. The results show that the likelihood of a better approval score is 22 percentage points lower if the first approval score is orange.[19] Sales of non-lending products increase the probability of a better approval with 2 percentage points, which is in line with the previous results in column (1) and (2). The paper does not find evidence that the credit volume affect the probability of a better approval score. One explanation for this result is that the credit volume is part of the approval algorithm and larger credit volumes result in a lower approval score. The paper also finds that loan officers use fewer trials and are less likely to improve the score for existing relationships, which is in line with Berg, Puri and Rocholl (2013). Overall, the evidence in Table III shows that the incentives of the loan

---

[18] Berg, Puri and Rocholl (2013) find a similar result that a one standard deviation increase of the loan size from the median increases the number of scoring trials with 11.9 percent.

[19] The two base cases are the first approval scoring outcomes green and red.

officers explain the number of scoring trials and the likelihood that the approval score improves.

In the next section the paper attempts to answer the question whether the delegation of authority affects the incentives of the loan officers to manipulate information.

5. The delegation of authority and information manipulation

Dessein (2002) predicts that the delegation of authority reduces the agent's incentives to manipulate information. In order to investigate the effect of the delegation of authority on information manipulation by loan officers the paper estimates the following difference-in-difference specification:

$$\begin{aligned} \text{Ln}(Number\ of\ trials_{ijkt}) \ &= \alpha + \delta_1 treated_j \times post_t + \\ &\delta_2 X_{ijkt} + \ \gamma_j + \gamma_t + \varepsilon_{ijkt,} \end{aligned} \qquad (2)$$

where the Ln($Number\ of\ trials_{ijt}$) is the natural logarithm of the number of scoring trials of credit application *i* at branch *j* by loan officer *k* at time *t*, $treated_j$ is a dummy variable which takes the value of one if the approval authority was delegated to the business director of branch j, $post_t$ takes the value of one if the credit application was done after the delegation of authority, X_{ijt} is a matrix of control variables, γ_j are branch fixed effects, γ_t are year-month fixed effects and ε_{ijt} is the error term. The matrix of control variables includes the outcomes of the first scoring trial (orange and red), firm characteristics (firm size, leverage and profitability), credit application characteristics (the natural logarithm of the new credit volume, the collateral ratio and the maturity) and relationship characteristics (lending relationship, lending from other banks, non-lending products). To address the problem of serially correlated outcomes in the differences-in-differences estimation (Bertrand, Duflo and Mullainathan, 2004) standard errors are clustered at the branch level.

Table IV reports the estimated coefficients of specification (2). Column (1) shows that the delegation of authority does not reduce the number of scoring trials. This result could imply that the delegation of authority does not affect the incentives of loan officers to manipulate information, or that it only affects the incentives of loan officers for a particular group of credit applications. Panel B of Figure 1 shows that risk management still approves the credit applications with a red approval score after the change, while a business director instead of a risk manager approves the credit applications with an orange approval score. This implies for this group of applications that the loan officer asks his direct superior for an approval of the credit application. The expectation is that in particular for orange and green scored credit applications the loan officer has fewer incentives to adjust the approval score. To examine this prediction the paper tests whether loan officers in the treated × post branches are less likely to use multiple scoring trials if the outcome of the first scoring trial is green or orange. Column (2) shows that loan officers use less scoring trials after the delegation of authority, but relatively more trials if the first approval score is red. Loan officers have an incentive to manipulate information to be able to submit the credit application to their own business manager. This interpretation assumes that the objective of the loan officer and the business director are more similar than the objectives of the loan officer and the risk manager. The previous section shows that loan officer specific characteristics are an important determinant of the number of scoring trials. The paper now tests whether the same loan officer has fewer incentives to manipulate information if the credit application will be approved by his business director. The paper estimates specification (2) with loan officer fixed effects and reports the results in column (3). The same loan officer uses less scoring trials after the delegation of authority, but similar to the results in column (2) uses more scoring trials if the first approval score is red. This confirms that loan officers try to get an approval from their business director instead of a risk manager which approves the credit applications with a red approval score.

An alternative measure for information manipulation is the better approval score dummy which takes the value of one if the final approval score is better than the first approval score. The paper tests whether the likelihood of a better approval score decreases after the delegation of authority by estimating the likelihood of a better approval score with a probit model. Note that this specification only includes the *orange* dummy and the interaction term treated × post × orange. This is because the dependent variable only varies if the first approval score is orange or red (it is not possible to improve a green approval score). Column (4) reports the marginal effects. The paper finds that the likelihood of a better approval score decreases with 9 percentage points if the first score is orange and the business director has the approval authority. Instead of improving the approval score, loan officer can refrain from adjusting a too positive approval score. To test this hypothesis, the paper estimates the likelihood that the approval score worsens between the first trial and the final trial. Column (6) shows that the likelihood of a negative change if the first approval score is orange increase with 13 percentage points after the delegation of authority. This result suggests that if their business director does not take the decisions loan officers add extra information to the credit application, which decreases the approval score.

The results suggest that loan officers are less likely to manipulate information if the credit application will be approved by their business director instead of a risk manager. In the next section the paper examines whether business directors make different approval decisions than risk managers if they face a similar credit application. This would explain why loan officers have fewer incentives to manipulate information.

6. The delegation of authority and the approval decision

The previous section shows that the delegation of authority reduces the loan officers' incentives to manipulate information. Economic theory, however, predicts that the delegation of authority comes with a loss of control (Dessein, 2002; Harris and Raviv, 2005; Marino and Matsusaka, 2005). The paper examines this claim by testing whether business directors make different approval decisions than risk managers.

The paper estimates the likelihood of a credit approval using the following specification:

$$\Pr(Approval)_{ijkt} = F(\alpha + \delta_1 treated_j \times post_t + \delta_2 X_{ijkt} + \gamma_j + \gamma_t), \quad (3)$$

where $\Pr(Approval)_{ijkt}$ is the likelihood of an approval of credit application i at the branch j by loan officer k at time t, $treated_j$ is a dummy variable which takes the value of one if the approval authority was delegated to the business director of branch j, $post_t$ takes the value of one if the credit application was done after the delegation of authority in October 2010, X_{ijt} is a matrix of control variables, γ_j are branch fixed effects, γ_t are year-month fixed effects. $F(.)$ is a standard normal cumulative distribution. The matrix of control variables includes the outcomes of the final scoring trial (orange and red), firm characteristics (firm size, leverage and profitability), credit application characteristics (the natural logarithm of the new credit volume, the collateral ratio and the maturity) and relationship characteristics (lending relationship, lending from other banks, non-lending products). To address the problem of serially correlated outcomes in the differences-in-differences estimation (Bertrand, Duflo and Mullainathan, 2004) standard errors are clustered at the branch level.

Table V presents the results of the estimation of specification (3) and reports the marginal effects. Column (1) shows that under delegation credit applications are less likely to get an approval. To control for differences in firm quality the paper includes the control variables in column (2) and show that the delegation of authority does not increase the likelihood of an approval. This result suggests that the delegation does not result in a significant loss of control in the sense that an average credit application has not a higher likelihood of an approval after the delegation. Even though the paper finds that business directors are not more likely to approve a credit application than a risk manager, they could still approve different credit applications than a risk manager would approve. To test this prediction the paper interacts the treated × post variable with the non-lending products dummy. The expectation is that business directors are more likely to approve credit applications with non-lending products. The results show that the probability of an approval increases with 25 percentage points if the firm purchases non-lending products and the business director makes the credit approval decision. In column (4) the paper interacts the treated × post variable with a dummy which takes the value of 1 if the credit application has an above average credit volume. Since the remuneration of the business director depends on the new credit volume the expectation is that business directors are more likely to approve credit applications with a high credit volume. However, the paper does not find evidence for this prediction.

The evidence in this section shows that business directors make a different credit decision than risk managers if a firm purchases non-lending products. This suggests that the objectives of the business director are similar to the objectives of the loan officers since the paper also finds that loan officers use more scoring trials if the firm purchases non-lending products and a risk manager makes the credit approval decision.[20] These two results provide evidence for Dessein's (2002) trade-off between a loss of information under communication and a loss of control under delegation. Dessein (2002) predicts that delegation is optimal for the principal if the bias in objectives between the principal and the agent is sufficiently small. The results of this paper do not show whether the bank was better off after the delegation of authority, but do show that the bias in objectives is an important consideration in the decision to delegate authority.

7. Placebo test

The results presented in the previous section could be driven by changes in the control and treatment branches unrelated to the delegation of authority. The bank officially divested the branches in the beginning of 2010 and the changes in the control branches after the divestment could drive the results.

[20] Agarwal and Hauswald (2010) show that a branch specific bias in the evaluation of borrowers predicts defaults, which reveals the cost of delegating authority in terms of loan losses. They calculate the branch specific effect in the borrower's internal credit rating and calculate the difference between the branch specific effect and the average branch effect and use this as a measure for the bias of the branch.

To test for this explanation the paper estimates the following specification:

$$\text{Ln}(Number\ of\ trials_{ijkt}) = \alpha + \delta_1 treated_j \times divestment_t + \delta_2 X_{ijkt} + \gamma_j + \gamma_t + \varepsilon_{ijkt,} \quad (4)$$

where the $\text{Ln}(Number\ of\ trials_{ijt})$ is the natural logarithm of the number of scoring trials of credit application *i* at branch *j* by loan officer *k* at time *t*, $treated_j$ is a dummy variable which takes the value of one if the approval authority was delegated to the business director of branch *j*, $divestment_t$ takes the value of one after the official divestment of the branches, X_{ijt} is a matrix of control variables, γ_j are branch fixed effects, γ_t are year-month fixed effects and ε_{ijt} is the error term. The matrix of control variables includes the outcomes of the first scoring trial (orange and red), firm characteristics (firm size, leverage and profitability), credit application characteristics (the natural logarithm of the new credit volume, the collateral ratio and the maturity) and relationship characteristics (lending relationship, lending from other banks, non-lending products). To address the problem of serially correlated outcomes in the differences-in-differences estimation (Bertrand, Duflo and Mullainathan, 2004) standard errors are clustered at the branch level.

Table VI presents the results. Although the results on the first approval score variables are similar to the results in Table IV, the coefficients on the interaction of the approval scores between the treated × divestment variable is not significant in all specifications. This suggests that the incentives of the loan officers to manipulate information did not change after the investments, which rules out the explanation that changes in the competitive landscape drive the result and not the organizational change.

8. Conclusions

The decision to delegate authority depends on the trade-off between a loss of information under communication and a loss of control under delegation. An agent could manipulate his private information if the principal makes the decision and has different objectives than the agent. The delegation of authority mitigates the problem of information manipulation, but this could result in a loss of control.

This paper empirically examines this trade-off by exploiting an organizational change in a small lending division in a large commercial bank in the Netherlands. In October 2010, the bank delegated the authority to approve small business loans from the risk management department to the business directors of local branches, except for a number of mandatory divested branches, which are used as control group.

The bank uses risk management software which scores the credit application and allows loan officers to make multiple scoring trials if the first scoring trial is not successful. The paper uses the number of scoring trials and the changes between the first and the final trial as empirical measures of information manipulation by loan officers. Based on a sample of more than 23,000 small business loan applications the paper tests whether the delegation of authority reduces the incentives of the loans officers to use multiple scoring trials and adjust the parameters of the credit application. The results show that loan officers use less scoring trials and are less likely to improve the approval score of the application if their own business director has the approval authority.

The paper tests whether the approval decision of a business director differs from an approval decision of a risk manager. The paper finds that the business director is more likely to approve a credit application with additional sales of non-lending products than a risk manager, which suggests that the delegation of authority could result in a loss of control.

The results suggest that the delegation of authority could mitigate the problem of information manipulation, but results in a loss of control if there are large differences in objectives. The implication of the results is that decision makers should carefully examine the differences in objectives between the decision maker and the information collecting agent and the potential of information manipulation before deciding to delegate authority.

Figure 1: The timeline of the divestment of the control group branches

Figure 1 presents the timeline of the divestment of the control branches and the delegation of authority at the treated branches.

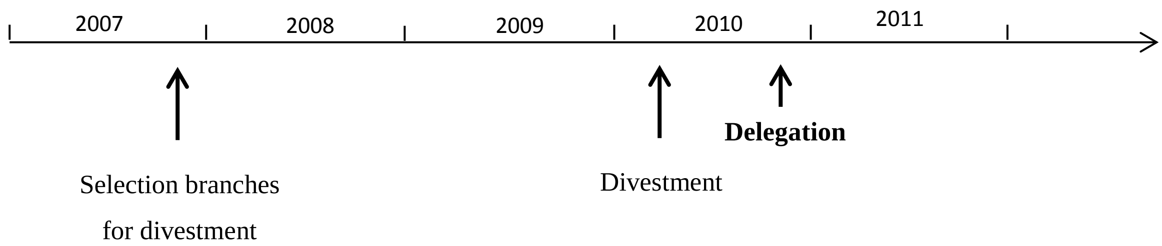
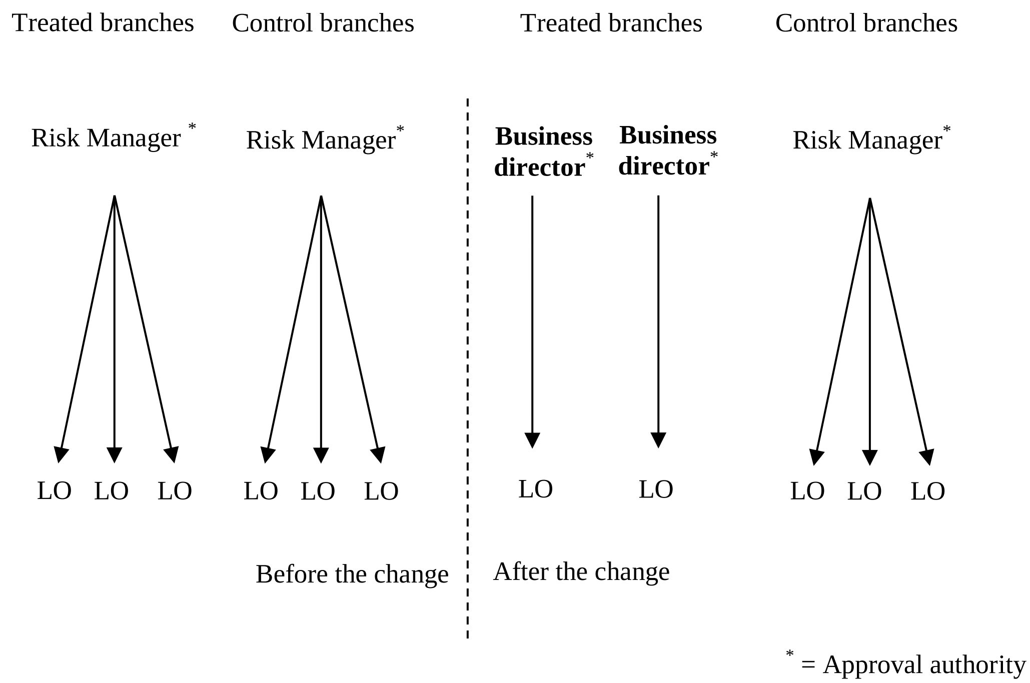


Figure 2: Delegation of the approval authority

Panel A in Figure 2 illustrates the allocation of the approval authority for the treated and control branches before and after the change. The approval authority is the decision maker which approves credit applications. The abbreviation LO stands for loan officer. The outcome of an algorithm (green, orange, and red) determines the approval authority. Panel B shows the allocation of the approval authority by the outcome of the algorithm for the treated and control branches before and after the change.

Panel A: The organizational change



Panel B: The allocation of the approval authority by approval score

Approval score				
Green	Automatic	Automatic	**Business director**	Automatic
Orange	Risk manager	Risk manager	**Business director**	Risk manager
Red	Risk manager	Risk manager	Risk manager	Risk manager

Table I: Summary statistics

Table presents the summary statistics of the variables employed in the empirical specifications and provides their mean, median and standard deviation for all 23,013 credit applications and for the treated and control branches separately. The definitions of the independent variables can be found in Appendix I. The paper uses a Student's t-test to assess the differences in means between the treated branches and control branches. The differences between the corresponding mean values of the treated and control branches are significant at the 10%, 5%, and 1% levels using *, **, and ***, respectively.

	Before the change				After the change				DID
	Treated		Non treated		Treated		Non treated		
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Firms characteristics									
Total assets (thousand euro)	672.4	3067	749.4	1023	684.2	2810	718.1	749	43.01
Profitability	0.33	0.65	0.19	0.39	0.321	0.672	0.21	0.52	-0.04
Firm age < 3 years	0.05	0.22	0.05	0.22	0.052	0.222	0.05	0.21	0.007
Firm age 3-8 years	0.20	0.40	0.19	0.39	0.187	0.390	0.19	0.39	-0.02
Firm age > 8 years	0.59	0.49	0.68	0.46	0.588	0.492	0.65	0.47	0.03
Credit demand	207.1	268.6	216.2	279.1	237.3	314.7	240.3	290.0	6.17
Real estate	0.263	0.403	0.251	279.1	0.271	0.40	0.255	0.39	0.005
Corporate investment	0.163	0.313	0.136	0.29	0.163	0.31	0.160	0.31	-0.03
Working capital	0.495	0.982	0.528	0.48	0.483	0.57	0.506	0.48	0.008
Relationship characteristics									
Lending relationship (0/1)	0.63	0.48	0.60	0.49	0.49	0.50	0.60	0.49	-0.03
Lending from other banks (0/1)	0.27	0.44	0.28	0.45	0.26	0.44	0.28	0.45	0.006
Observations	7,801		1,202		4,709		545		

Table II: Information manipulation measures

Table II presents the summary statistics for the information manipulation measures of all 23,013 credit applications and conditional on the first approval score. The first approval score (Green, Orange, Red) is the outcome of the first scoring trial of an algorithm which determines the approval authority. The definitions of the variables can be found in Appendix I.

	(%)	Number of trials (#)	Better approval score (%)	Worse approval score (%)
All credit applications	100.0	9.81	14.7	3.9
First approval score				
Green	9.5	8.21	0.0	16.6
Orange	64.9	9.73	7.12	3.5
Red	25.6	10.61	39.3	0.0

Table III: Information manipulation

$$Ln(Number\ of\ trials_{ijkt}) = \alpha + \delta_2 X_{ijkt} + \gamma_j + \gamma_t + \varepsilon_{ijkt}$$

Table III presents the results from regressions with the natural logarithm of the *number of trials* as dependent variable in column (1) and (2) and the dummy *better approval score* in column (3), which takes the value of one if the approval score improves between the first and last scoring trial. The sample includes all 23,013 credit applications. The definitions of the independent variables can be found in Appendix I. In addition, the baseline specification includes 192 branch dummies, 11 credit rating dummies, 29 year-month dummies and 13 industry dummies. The dependent variable is estimated with OLS in columns (1) and (2) and a probit model in column (3). The table reports the regression coefficient in columns (1) and (2) and the marginal effects in column (3). Statistical significance at 10%, 5% and 1% levels is denoted by *, **, *** respectively . Standard errors are robust and clustered at the branch level.

	(1)	(2)	(3)
Dependent variable:	Ln Number of trials	Ln Number of trials	Better approval score
Model:	OLS	OLS	Probit
First approval score			
Orange	0.171***	0.180***	-0.226***
	(0.018)	(0.018)	(0.010)
Red	0.247***	0.257***	
	(0.022)	(0.021)	
Firm characteristics			
Firm size	-0.000	0.029***	0.000
	(0.007)	(0.006)	(0.003)
Leverage	-0.038***	-0.017	-0.004
	(0.014)	(0.014)	(0.006)
Profitability	-0.007	0.004	0.001
	(0.010)	(0.010)	(0.004)
Relationship characteristics			
Lending relationship	-0.031**	0.005	-0.020***
	(0.013)	(0.013)	(0.006)
Lending from other banks	0.036***	0.010	-0.006
	(0.014)	(0.012)	(0.005)
Non-lending products	0.353***	0.402***	0.018***
	(0.014)	(0.011)	(0.005)
Credit application characteristics			
Ln New credit volume	0.059***	0.066***	0.001
	(0.005)	(0.005)	(0.002)
Collateral ratio	0.119***	0.105***	0.052***
	(0.014)	(0.014)	(0.006)
Maturity	0.005***	0.004***	0.001***
	(0.001)	(0.001)	(0.000)
Branch FE	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes
Year - month FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Loan officer FE		Yes	
(adj.) R-squared	0.128	0.269	0.157
Observations	23,013	23,013	23,013

Table IV: Delegation of authority and information manipulation

$$\boldsymbol{Ln(Number\ of\ trials_{ijkt})\ = \alpha + \delta_1 treated_j \times post_t + \delta_2 X_{ijkt} + \gamma_j + \gamma_t + \varepsilon_{ijkt}}$$

Table IV presents the results from regressions with the natural logarithm of the *number of trials* as dependent variable in column (1) to (3) and the dummy *better approval score* in column (5), which takes the value of one if the approval score improves between the first and last scoring trial. The sample includes all 23,013 credit applications. The control variables include firm characteristics (firm size, leverage, profitability), credit application characteristics (the natural logarithm of the new credit volume, the collateral ratio and the maturity) and relationship characteristics (lending relationship, lending from other banks, non-lending products). The definitions of the independent variables can be found in Appendix I. In addition, the baseline specification includes 192 branch dummies and 29 year-month dummies. The dependent variable is estimated with OLS in columns (1) to (3) and a probit model in columns (4) and (5). The table reports the regression coefficient in columns (1) to (3) and the marginal effects in columns (4) and (5). Statistical significance at 10%, 5% and 1% levels is denoted by *, **, *** respectively . Standard errors are robust and clustered at the branch level.

	(1)	(2)	(3)	(4)	(5)
Dependent	Ln Number of trials	Ln Number of trials	Ln Number of trials	Better approval score	Worse approval score
Model	OLS	OLS	OLS	Probit	Probit
First approval score					
Orange	0.184***	0.172***	0.166***	-0.177***	-0.023***
	(0.020)	(0.021)	(0.019)	(0.007)	(0.003)
Red	0.236***	0.198***	0.197***		
	(0.024)	(0.027)	(0.023)		
Treated × Post	0.051	-0.073	-0.080	0.060***	-0.042***
	(0.042)	(0.061)	(0.063)	(0.019)	(0.004)
Treated × Post × Orange		0.093	0.106**	-0.089***	0.127***
		(0.057)	(0.051)	(0.006)	(0.019)
Treated × Post × Red		0.171***	0.194***		
		(0.049)	(0.052)		
Control variables	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes
Year - month FE	Yes	Yes	Yes	Yes	Yes
Loan officer FE			Yes		
(adj.) R-squared	0.125	0.125	0.268	0.138	0.075
Observations	23,013	23,013	23,013	23,013	23,013

Table V: Delegation of authority and the approval decision

$$\Pr(Approval)_{ijkt} = F(\alpha + \delta_1 treated_j \times post_t + \delta_2 X_{ijkt} + \gamma_j + \gamma_t)$$

Table V presents the results from regressions with *application approved* as dependent variable. The sample includes all 23,013 credit applications. The control variables include firm characteristics (firm size, leverage, profitability), credit application characteristics (the natural logarithm of the new credit volume, the collateral ratio and the maturity) and relationship characteristics (lending relationship, lending from other banks, non-lending products). The definitions of the variables can be found in Appendix I. In addition, the baseline specification includes 192 branch dummies and 29 year-month dummies. The dependent variable is estimated with a probit model and the table reports the marginal effects. Statistical significance at 10%, 5% and 1% levels is denoted by *, **, *** respectively . Standard errors are robust and clustered at branch level.

	(1)	(2)	(3)	(4)
Treated × Post	-0.079**	-0.006	-0.184***	-0.008
	(0.031)	(0.023)	(0.031)	(0.028)
Treated × Post × Non-lending products			0.258***	
			(0.016)	
Treated × Post × Above median new credit volume				0.002
				(0.019)
Control variables		Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
Year – month FE	Yes	Yes	Yes	Yes
R-squared	0.047	0.276	0.285	0.272
Observations	23,013	23,013	23,013	23,013

Table VI: Placebo test

$$\boldsymbol{Ln(Number\ of\ trials_{ijkt})\ = \alpha + \delta_1 treated_j \times divestment_t + \delta_2 X_{ijkt} + \ \gamma_j + \gamma_t + \varepsilon_{ijkt}}$$

Table VI presents the results from regressions with the natural logarithm of the *number of trials* as dependent variable in column (1) to (3) and the dummy *better approval score* in column (5), which takes the value of one if the approval score improves between the first and last scoring trial. The sample includes all 23,013 credit applications. The control variables include firm characteristics (firm size, leverage, profitability), credit application characteristics (the natural logarithm of the new credit volume, the collateral ratio and the maturity) and relationship characteristics (lending relationship, lending from other banks, non-lending products). The definitions of the independent variables can be found in Appendix I. In addition, the baseline specification includes 192 branch dummies and 29 year-month dummies. The dependent variable is estimated with OLS in columns (1) to (3) and a probit model in columns (4) and (5). The table reports the regression coefficient in columns (1) to (3) and the marginal effects in columns (4) and (5). Statistical significance at 10%, 5% and 1% levels is denoted by *, **,*** respectively . Standard errors are robust and clustered at the branch level.

	(1)	(2)	(3)	(4)	(5)
Dependent	Ln Number of trials	Ln Number of trials	Ln Number of trials	Better approval score	Worse approval score
Model	OLS	OLS	OLS	Probit	Probit
First approval score					
Orange	0.22***	0.22***	0.21***	-1.02***	0.083***
	(0.018)	(0.018)	(0.012)	(0.051)	(0.023)
Red	0.28***	0.288***	0.293***		
	(0.023)	(0.020)	(0.013)		
Treated × Divestment	-0.013	0.024	0.051	-0.023	0.078
	(0.030)	(0.043)	(0.050)	(0.051)	(0.098)
Treated × Divestment × Orange		-0.030	-0.045	0.008	0.137
		(0.046)	(0.045)	(0.065)	(0.155)
Treated × Divestment × Red		-0.057	-0.061		
		(0.046)	(0.053)		
Control variables	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes
Year - month FE	Yes	Yes	Yes	Yes	Yes
Loan officer FE			Yes		
(adj.) R-squared	0.124	0.108	0.230	0.15	0.03
Observations	23,013	23,013	23,013	23,013	23,013

Appendix I: Variable definitions

Variable name	Definition
Firm characteristics	
Total assets	Total assets from the latest annual report, in thousand euro.
Leverage	Total liabilities / total assets.
Profitability	EBIT / total assets.
Credit rating	Firm credit rating ranging from 2 (no problems) to 5 (potential problems).
Relationship characteristics	
Lending relationship	= 1 if the firm has an existing lending relationship with the bank and 0 otherwise.
Lending from other banks	= 1 if the firm has debt from other banks and 0 otherwise.
Non-lending products	= 1 if the firm purchases non-lending products from the bank and 0 otherwise.
Credit application characteristics	
New credit volume	New credit volume of the credit application, in thousand euro.
Collateral ratio	Total collateral value / Total credit volume.
Maturity	Facility size weighted average maturity of the credit application, in years.
Interest spread	Facility size weighted average interest spread of the credit application, in basis points.
Credit approval characteristics	
First approval score	
Green	= 1 if the first approval score is green and 0 otherwise. The first approval score (Green, Orange, Red) is the outcome of the first scoring trial of an algorithm which determines the approval authority.
Orange	= 1 if the first approval score is orange and 0 otherwise. The first approval score (Green, Orange, Red) is the outcome of the first scoring trial of an algorithm which determines the approval authority.
Red	= 1 if the first approval score is red and 0 otherwise. The first approval score (Green, Orange, Red) is the outcome of the first scoring trial of an algorithm which determines the approval authority.
Number of trials	Number of scoring trials for a credit application.
Better approval score	= 1 if the final approval score is better than the first approval score and 0 otherwise.
Worse approval score	= 1 if the final approval score is worse than the first approval score and 0 otherwise.
Application approved	= 1 if the credit application has been approved and 0 otherwise.

II Bargaining with a Bank

Abstract

This paper studies firm bargaining behavior in the credit market using a unique hand-collected data set on 18,591 credit negotiations between small firms and a large commercial bank. In a typical credit negotiation the firm and the bank firstly sets the collateral requirements, then the non-interest credit terms of the credit lines and term loans and finally the interest rates and fees. The bank extracts rents in the first offer from relationships and opaque firms and these firms are less likely to negotiate interest rate concessions, which suggest that informational frictions in the credit market give banks bargaining power. Negotiating firms pay a 33 basis points lower interest rate than otherwise similar firms which accept the first offer.

1. Introduction

The terms of credit contracts are often subject to negotiation. In negotiations the credit terms are set depending on the relative bargaining power of the firm and the bank. The distribution of bargaining power between firms and banks, affects investment decisions, choices of financing sources and entrepreneurial effort (Inderst and Müller, 2004; Rajan, 1992).[1] Although bargaining power is important in financial decision making, there is little empirical research on bargaining behavior in credit negotiations. Data on real world negotiations is difficult to obtain because they take place in private meetings, on the phone or by e-mail.[2] Consequently, a number of important questions remain unanswered: How and when are credit terms set in negotiations? Do lending relationships and firm opaqueness affect bargaining behavior?

This is the first paper that examines bargaining behavior in the small business credit market, using a unique hand collected data base including detailed information about the negotiation process. The small business credit market provides a useful empirical setting to study bargaining behavior. First, proprietary information about opaque small firms could give a bank an informational advantage over its competitors (Sharpe, 1990; Rajan, 1992). This informational advantage gives the bank bargaining power. Second, the existing literature shows that small business interest rates exhibit substantial dispersion, even after one takes into account the differences in firm, loan, relationship and market characteristics (e.g. Cerqueiro, Degryse and Ongena, 2011). Interest rate dispersion suggests that frictions in the credit market enable banks to negotiate firm specific interest rates, depending on their relative bargaining power.

Central to this study is a data set of 18,591 credit negotiations between small firms and one large commercial bank in the Netherlands during the period January 2008 -

---

[1] Bargaining power does not only affect the financial decisions of firms. A growing theoretical literature investigates the effects of bargaining in decentralized financial markets (e.g. Duffie, Gârleanu and Pedersen, 2005; 2007) and shows that the distribution of bargaining power affects the prices and allocation of assets.

[2] Several papers have examined bargaining in retail transactions. Morton, Zettelmeyer, and Silva-Risso (2004) compare survey data on buyer characteristics and price/purchase outcomes from car dealerships and Ayers and Siegelman (1995) use an audit survey methodology to test for discrimination against blacks and women in bargaining for cars. However, there is no study which focuses on bargaining behavior between firms in a non-experimental real world setting.

December 2011. The bank is one of the top five commercial banks in the Netherlands and its business practices, information acquisition and loan data are highly representative for the banking industry in the U.S. and Europe. The lending software of the bank records a time stamp when loan officer create the credit terms of the offer, e.g. the collateral requirements, and a time stamp of the last update of the terms, which enables to study when the individual credit terms are set. In addition, the lending software records both the credit terms of the first offer and the credit agreement. This enables to study how the bank sets the first offer, which firms reach an agreement and negotiate better terms.

The paper analyses the order at which loan officers set the credit terms in the negotiation. Most empirical studies on borrowing costs and collateral assume that collateral and interest rate conditions are determined sequentially, with the collateral decision preceding the interest rate determination (Degryse, Kim and Ongena, 2009). This paper shows that in 87 percent of the negotiations the firm and the bank first set the collateral requirements, then the non-interest credit terms of the credit lines and term loans and finally the interest rates and fees of the facilities. After the approval of the credit offer, the firm and the bank most frequently negotiate about the interest rates and fees. These findings stress the importance of collateral in the design of credit contracts and confirm that the interest is the last term set in negotiations. The paper does not find evidence that the firm and the bank tradeoff collateral and interest rates.

An important puzzle in the empirical banking literature is whether the length of the relationship between the firm and the bank increases or decreases the firm's cost of credit. The private information which the bank collects over the relationship could give the bank an informational monopoly and enable them to extract informational rents from good firms (Sharpe, 1990; Rajan, 1992). On the other hand, relationships could reduce information asymmetries between the firm and the bank and therefore reduce the cost of credit of small firms (Boot and Thakor, 1994). The empirical literature on banking relationships analyses the outcomes of credit negotiations but finds mixed evidence. [3]

[3] See Degryse, Kim, and Ongena (2009) for an overview of the empirical evidence on the effect of lending relationships on firm bargaining power.). Many studies run reduced-form regression of the firm's cost of credit on the duration of the bank-firm relationship. Some studies find that interest increase over the

This paper is the first paper which studies the negotiation process and the impact of relationships on bargaining behavior. The paper finds that the interest rate of the first offer to relationships is 30 basis points higher than the interest rate of new clients of the bank. In addition, relationships are 3 percent less likely to negotiate an interest decrease, and are more likely to reach an agreements then similar firm without relationship applying for a similar credit facility. The bank uses information collected over the course of the lending relationship, such as the credit line usage and transaction account behavior, to discriminate between "good" and "bad" firms in the first offer. Bad firms are less likely to negotiate a lower interest rate, which is consistent with "informational capture" theories.

A large literature in corporate finance examines how asymmetric information in the process of raising external capital can generate financial constraints for firms.[4] Financially constraint firms have less access to competing offers when searching for outside finance and therefore should have less bargaining power in the credit market. This paper tests this prediction by examining whether larger and older firms receive a better first offer and are more likely to negotiate interest rate concessions. Hadlock and Pierce (2010) show that in particular small and young firms are financially constraint because these firms have a shorter track record and do not always have audited annual reports. The paper finds that large and older firms receive a first offer with a lower interest rate and are more likely to negotiate a lower interest rate, which suggest that these firms have indeed more bargaining power in the credit market.

A firm possesses bargaining power if the firm can affect the bargaining outcome in a way desirable for him. If interest decreases in negotiations actually capture firm bargaining power, negotiating firms should pay a lower interest rate than similar firms which accept the first offer. The results show that negotiating firms pay an interest rate

---

duration of the relationship, while others find the relationship duration does not matter or the cost of credit decreases over the lending relationship. Explanations for these mixed results are differences in the included control variables, definitions of firm-bank relationships, empirical measures of the cost of credit and composition of the pool of borrowers (Degryse, Kim, and Ongena, 2009

[4] See Hadlock and Pierce (2010) for an overview on the literature on the measurement of financial constraints and Almeida and Campello (2007) for an overview on the literature on the impact of financial constraints on corporate investment.

which is 33 basis points lower than similar firms which accept the first offer of the banks. Conversations with loan officers tell that “a quarter” (25 basis points) is a common discount they give in negotiations, which is close to the estimated coefficient. The results also show that the magnitude of the negotiated discount depends on firm characteristics. The negotiated discount is smaller for large firms. One explanation for this finding is that banks face more competition when offering credit to larger firms and therefore make a better offer in the first place. Since the height of the first offer determines the room to negotiate, a more competitive first offer allows the bank only to decrease the interest with a smaller amount. This is consistent with the finding that larger firms receive a lower interest rate in the first offer.

The primary contribution of this study is to provide the first empirical evidence on the negotiation process and bargaining behavior. The papers is related to the literature on the impact of relationships on the cost of credit. Closest to this paper are Aggarwal and Hauswald (2010), Ioannidou and Ongena (2010) and Bharath, Dahiya, Saunders and Srinivasan (2011). Aggarwal and Hauswald (2010) show that banks strategically use their local information advantage to create adverse-selection threats for their rivals, which gives them more bargaining power. Ioannidou and Ongena (2010) show that switching firms pay a lower interest rate at their new bank than similar firms which do not switch, but face an increase the interest rate over time. This paper shows that bank use privately collected information in credit negotiations and have bargaining power over relationships and opaque firms. Bharath, Dahiya, Saunders and Srinivasan (2011) show that lending relationships yield substantial benefits in the syndicating loan market. One explanation for this different finding is that firms in the syndicated loan market are larger and more transparent. Stronger competition in the syndicated loan market may force banks to pass on monitoring costs savings to the borrower.

This study is also related to a growing number of empirical studies on the design of credit contracts. Berger, Frame and Ioannidou (2011) and Cerqueiro, Roszbach, and Ongena (forthcoming) show that collateral has an important impact on the supply and cost of bank credit, bank monitoring incentives and that collateral reduces ex ante information asymmetries and ex post incentive problems between borrowers and lenders.

This study shows that in a typical credit negotiation the bank and the firm firstly set the collateral and thereafter the other credit terms, which suggests that collateral is important in the negotiation process.

The rest of this paper proceeds as follows. Section 2 discusses hypotheses, Section 3 the data, the negotiation process and the descriptive statistics. Section 4 and 5 the results and Section 6 concludes.

2. Theoretical predictions

Do lending relationships and firm opaqueness affect bargaining behavior? The bargaining behavior of the bank and the firms comprises the first offer of the bank to the firm, the concessions made in the negotiations and the likelihood that the negotiations results in an agreement. The goal of this section is to answer this question in order to motivate and guide the empirical analysis that follows.

2.1 The effect of relationships on bargaining behavior

2.1.1 The effect of relationships on the first offer of the bank

Relationship banks gather customer-specific information over time through multiple interactions (Boot, 2000). This information, such as information on checking account activity of the firm (Norden and Weber, 2010), is proprietary and not observable by other banks. Private information reduces adverse selection concerns, but also affects the competition between the relationship bank and outside banks which do not lend to the firm. Relationship banks could identify “good” and “bad” firms based on their private information, while these firms are observationally identical for all banks which do not lend to these firms. In credit negotiations they exploit this informational advantage by extracting informational rents from “good” firms (Sharpe, 1990; Rajan, 1992; Von Thadden, 2004). Therefore, these “informational capture” theories predict that banks have bargaining power over their relationships in credit negotiations. The private information of the bank should therefore predict the first offer of the bank.

Alternatively, the private information of relationship banks reduces information asymmetries and therefore the screening and monitoring costs of the bank. The relationship lender could share or pass on these cost savings to the firm and which reduces the borrowing costs for relationships (Boot and Thakor, 1994). This allows the relationship bank to make a better first offer to their relationships.

This paper uses the first offer all-in interest rate as the measure of the interest rate charged on a loan. The first offer all-in interest rate measures the interest rate plus any associated fees of the first credit offer to the firm. If bank exploit their informational advantage, they would make a higher first offer to relationships. In addition, this paper uses two variables which the bank could only observe over the course of the relationship: the first measure captures whether the bank has in general a good experience with the firm and the second measure is an internal credit rating based on the credit line usage and transaction account behavior of the firm. Mester, Nakamura, and Renault (2007) and Norden and Weber (2010) show that this information is used by banks in monitoring and lending decisions. The empirical section of this paper will discuss the two measures in detail. Informational capture theories predict that banks use this information and make different offers to “bad” and “good” firms which are observably equivalent for other banks. Specifically, the paper tests the following two hypotheses:

H.1. The first offer to relationship firms has a higher all-in interest rate relative to non-relationship firms.

H.2. The bank uses its private information in negotiations by making a better first offer to “good” firms.

2.1.2 The effect of relationships on concessions

After having received the first offer, the firm could directly accept the first offer, negotiate better terms or accept the offer of another bank. Traditional bilateral bargaining models (e.g. Rubinstein and Wolinsky, 1985) predict that the bank observes the bargaining power of the firm and sets a first offer which the firm directly accepts. Bank competition models often assume that banks make a sealed bid offer to the firm where after the firm accepts the best offer.[5] In these models multi stage negotiations with concessions do not occur.

An important feature of a credit offer which could explain multi stage negotiations is the expiration date of the offer. In contrast with strategic bargaining theories, which assume that parties directly accept or reject an offer, a credit offer expires after a pre-determined period. For example, in practice credit offers often expire in two weeks. When there is ex ante uncertainty about the bargaining power of the firm and offers expire after a pre-determined period, the bank optimally sets a high first offer and after the uncertainty about the outside options of the firm has been resolved the bank improves the offer of firms with better outside offers and firms without outside offers accept the first offer of the bank.[6]

The informational advantage of the relationship bank reduces the likelihood that a relationship firm receives better outside offers and is therefore less likely to negotiate and interest decrease. Von Thadden (2004) shows that relationship banks make offers to “bad” firms which equal their marginal lending costs and extract an informational rent from “good” firms. Since the relationship bank does not extract profit from bad firms, they could not make concessions to them in credit negotiations. If the bank makes concessions, it will be to the good firms. These predictions result in the following two hypotheses:

H.3. Firms with a lending relationship are less likely to negotiate.

H.4. Banks will only make concessions to “good firms”.

Although lower screening and monitoring costs for relationships could result in a lower first offer interest rate, these relationship benefits are unlikely to change over the negotiation. In addition, the underlying credit risk of small firms is also unlikely to

---

[5] See for example Sharpe (1990) or Rajan (1992).

[6] Lee (1994) and Chatterjee and Lee (1998) show that in a market in which firms could ‘recall’ their first offer and uncertainty about the outside options of the firm, negotiations with more than one offer can occur in equilibrium.

change. Therefore, hypothesis 3 and 4 are a clean test for the predictions of "informational capture" theories (Sharpe, 1990; Rajan, 1992).

There are three alternative explanations why banks make concessions in credit negotiations. Firstly, the firm might provide new information to the bank, for example a new annual report, which changes the bank's estimate of the creditworthiness of the firm and convinces the bank to improve the offer because of lower risk. Secondly, financial contracting theories predict that a trade-off between collateral requirements and the interest rate could resolve information asymmetries between the bank and the firm (Bester, 1980). Changes in credit terms over the negotiation could reflect these trade-offs. Thirdly, the bargaining ability of the loan officer affects bargaining behavior in credit negotiations. The empirical part of this paper tests whether these alternative explanations could explain changes in credit terms over the negotiation.

2.3 The effect of relationships on the likelihood of an agreement

Relationships affect the likelihood that the firm reaches an agreement with the bank. Von Thadden (2004) shows that outside banks limit the bargaining power of the relationship bank by offering competing lower interest rates using "optimal randomization" to the firms from the relationship bank. As a result "bad" firms and occasionally "good" firms switch to the outside bank if the outside bank offers them a better deal. Therefore, relationships are more likely to accept the credit offer of the bank; in particular the good firms because they receive only sporadically receive a good offer from outside banks. This prediction results in the following hypothesis:

H.5. Relationships are more likely to reach an agreement with relationships and this likelihood is higher if the bank has positive private information about the firm.

Although hypothesis 3, 4 and 5 are a prediction on the effect of relationships on the bargaining behavior of the firm, they to not predict when the firm decides to accept the negotiated offer and when the firm decides to accept the offer of the other bank. A rational firm would accept the best offer, taking into account the switching cost to move to another bank. The empirical analysis which will follow will examine whether firms with bargaining power prefer to negotiate or to switch.

2.2 The effect of opaqueness on bargaining behavior

A large literature in corporate finance examines how asymmetric information in the process of raising external capital can generate financial constraints for firms. Financially constraint firms have less access to competing offers when searching for outside finance and therefore should therefore have less bargaining power in the credit market. This paper tests this prediction by examining whether the size and age of the firm affect their bargaining behavior. Hadlock and Pierce (2010) show that in particular small and young firms are financially constraint because these firms have a shorter track record and do not always have audited annual reports. Therefore, opaque firms will receive a higher first offer, are less likely to negotiate and are more likely to reach an agreement with the bank. The paper tests the following hypothesis:

H.6. Opaque firms have less bargaining power in credit negotiations.

3. Negotiation data

3.1 The sample

The sample consists of 18,591 credit negotiations between 15,909 non-financial, small firms and a large commercial bank over the period January 2008 - December 2011.[7] The bank is one of the top five commercial banks in the Netherlands and its business practices, information acquisition and loan data are highly representative for the banking industry. The Netherlands has a bank-based financial system, but is similar to the U.S. in general economic, financial, and technological development. Although the market structure of the banking sector is relatively concentrated, the largest banks have branches

[7] The sample period overlaps the 2007-2009 credit crisis. However, the decrease in aggregate corporate credit growth in the Netherlands was less severe in comparison with other European countries and the lending standards of Dutch banks followed a similar trend as the lending standards in the Eurozone (DNB, 2012).

in each region and are not geographically concentrated.[8] The cultural values in the Netherlands, which could affect bargaining behavior (Roth, Prasnikar, Okuno-Fujiwara and Zamir, 1991), are very similar to the U.S. compared to other European countries (Hofstede, 1991).

The firms in the sample are small and medium sized firms, such as farms, wholesalers, construction firms, architect bureaus and medical practices. The firms have a mean total asset size of 607 thousand euro, 3 employees and are comparable with small U.S. firms covered by the 2003 National Survey of Small Business Finance (NSSBF).[9] Firms have in 66 percent of the negotiations an existing relationship with the bank and in 24 percent of the negotiations bank debt from other banks. The average (median) new credit demand of the firms is 227 (145) thousand euro.[10] Both prospective and existing customers apply for new credit, new facilities are no renewal or adjustment of existing facilities and the firms in the sample are not in default. Therefore, this study does not focus on renegotiation of existing contracts or ex post bargaining in payment default or bankruptcy.[11]

3.2 The negotiation process

The negotiation process starts with a meeting in which the firm and the loan officer discuss the credit demand and business prospects. Based on the discussion with the firm the loan officer structures the draft credit offer. The draft credit offer consist of the general terms and conditions, the collateral requirements and for one or more credit facilities, such as credit lines and term loans, the facility size, maturity, and installments. For each facility, the loan officer sets the interest rate and the fees. Once the loan officer

---

[8] The assets of the three largest commercial banks comprise 71 percent of the asset of all commercial banks in 2010 (Beck and Demirgüç-Kunt, 2008). In Belgium this concentration ratio is 83 percent, while in Germany the three largest commercial banks comprise 38 of the asset of all commercial banks. However, in the banking system in Germany consist besides commercial bank of many large state-owned banks.

[9] The median firm in the NSSBF survey has an asset size between 100 and 240 thousand dollar and employs five to nine employees (Mach and Wolken, 2006).

[10] In the credit application, before the approval decision of the bank, firms specify their new credit demand and the specific purpose of their credit demand.

[11] Roberts and Sufi (2009) analyze renegotiations in a sample of 1,000 syndicated loan contracts. Gilson (1990), Gilson, John and Kang (1990), Asquith, Gertner, and Scharfstein (1994), and Benmelech and Bergman (2008) study the outcomes of ex post bargaining in the event of payment default or bankruptcy.

finishes the draft credit offer, he submits the draft credit offer for approval. After the approval, the loan officer prepares the official credit offer. The credit offer is an actual credit contract, signed by the bank, and expires after fourteen days. During this 14-day period, the firm could directly accept the offer, negotiate better terms with the bank or decide not to accept the offer. Loan officers do not have incentives to negotiate before the first offer. Negotiating before the approval decision violates the bank's procedures and puts the loan officer's reputation at stake.

3.3 Summary statistics of the negotiation process

The main data source of the negotiation data is the lending software of the bank. The loan officers use the lending software to specify the credit term of the credit offer and could not make offers outside this system.[12] However, loan officers have discretion to set all the credit terms. A special feature of the lending software is that it records a time stamp when the loan officer creates the terms of the offer, e.g. the collateral requirements, and a time stamp of the last update of the terms. This enables to study in detail the order at which the individual credit terms are set. In addition, the software saves all the credit terms after the approval of the credit offer. Any change in the credit terms after the approval result automatically in a new version of the credit offer. This feature of the data allows studying the negotiation process after the first offer. The data does not include intermediate offers between the first offer and the agreement and does not include offers of other banks.

The paper firstly analyses the order at which the loan officer sets the credit terms of the credit offer. Most empirical studies on borrowing costs and collateral assume that collateral and interest rate conditions are determined sequentially, with the collateral decision preceding the interest rate determination (Degryse, Kim and Ongena, 2009).[13]

[12] This system is similar to the lending software described in Agarwal and Hauswald (2010) and Berg, Puri and Rocholl (2013). Specialized firms, such as TCI Loan origination solutions, Lenders Logic and Global Wave Banking Solutions offer similar specialized software packages to commercial banks for loan origination, workflow, approval and monitoring of commercial loans.

[13] See Degryse, Kim and Ongena (2009) for a detailed overview on the large literature studying the terms of a credit contract. Examples are Petersen and Rajan (1994; 1995), Berger and Udell (1995), Degryse and Ongena (2005) and Agarwal and Hauswald (2010). Brick and Palia (2007) relax the assumption that

The negotiation data of this paper offers a unique opportunity to test this implicit assumption. It is important to note that lending software does not force the loan officer to enter the credit terms in pre-specified order. The loan officer could go back and forward in the credit writing software and is therefore not bound by a fixed order of the steps.

Panel A of Table II shows the mean and median time between the first meeting between the firm and the loan and the last update of the collateral requirements, the facilities (size and maturity of the credit lines and term loans) and the pricing of the credit offer (all interest rates and fees). Loan officers firstly finish the collateral requirements in on average 17 days after the first meeting, complete the facilities of the credit offer after 18 days and the interest rates and fees of the credit offer 21 days after the first meeting. Using the time stamps of the last update it is possible to determine the order in which the credit terms are set. Panel B shows that in 87 percent of the first offers the loan officer sets the collateral first, then the facilities and finally the interest rate. In 13 percent of the first offers, the loan officer sets first the facilities, then the collateral and finally the interest rate. These findings show that the interest rate is the last term set in credit negotiations. Existing research show the importance of collateral to reduce ex ante information asymmetries and ex post incentive problems between borrowers and lenders (Berger, Frame and Ioannidou, 2011). The result that in most negotiation collateral is set first confirms the important role of collateral in the design of credit contracts. When distinguishing between relationships and new clients, the table shows that in almost all negotiations with existing relationships collateral is set first. Relationships pledged often already collateral for existing credit lines and term loans and add new loans while keeping the collateral the same. This is in line with the evidence that relationships pledge less collateral (Berger and Udell, 1995; Chakraborty and Hu, 2006; Degryse and Cayseele, 2000).

Loan officers could only make a first offer after an approval by the risk management department. The first offer consists of a general credit agreement, including the description of the parties, the general conditions of the credit contract, covenants and

---

collateral and the interest rate are set independently and estimate a system of two equations and find evidence for jointness in the credit terms.

the collateral requirements, and the credit terms of the individual facilities (credit lines and term loans). The loan officer specifies for each new facility (credit lines and term loans) the facility size, the maturity and the installments. Table III presents the descriptive statistics of the new facilities in the first offer. The new facility is in 37 percent of the facilities a credit line and the remaining facilities are term loans. The average facility has a size of 137 thousand euro, a maturity of 7 years and a collateral ratio of 81 percent. In small business lending financial covenants are hardly used because of the high monitoring costs. In general, the bank uses the credit line usage and transaction account behavior to monitor small firms because this information could be processed automatically at lower costs. The average interest rate is 621 basis points and includes fees.

The right section of Table III presents the summary statistics of the credit facilities of the credit agreements and shows that 80 percent of the facilities are accepted by the firms.[14] The average facility size of the facilities is smaller which suggest that firms are less likely to reach an agreement on larger facilities. For all the agreements, the paper calculate the difference in credit terms of the facilities between the first offer and the agreement and defines two dummy variables which take the value of one if the credit term increased (decreased) and zero otherwise. The most frequent credit term change is an *interest decrease* (15 percent of the negotiations), while the new credit volume, collateral value and maturity change in less than 3 percent of the negotiations. The other credit terms change in both directions, however most credit volume and most collateral changes change in firm favorable directions. Since changes in other credit terms than the interest rate occur relatively infrequent there is little scope to identify a single economic mechanism driving these changes.[15] The average negotiation time is 13 days which shows that the bank and the firm reach an agreement in a relative short period.

---

[14] Firms which do not reach an agreement either accept an offer of another bank or withdraw from the credit market. Firms do not report whether they accepted an offer of another bank. Since it is not possible to observe the credit term changes of negotiations which do not result in an agreement, the data is incidentally truncated. To address this potential selection problem, the paper estimates a heckman selection problem and finds that selection does not change the results.

[15] Roberts and Sufi (2009) show that in renegotiations of syndicated loans also the amount and the maturity frequently changes in directions favorable to the borrower. A difference between Roberts and Sufi (2009) is

Financial contracting theories suggest that the bank could offer a menu of contracts to resolve ex ante information asymmetries. Specifically, banks could offer a menu of collateral requirements and interest rates such that observationally equivalent firms with higher quality projects choose secured loans with a low interest rate, while firms with low quality projects self-select into unsecured loans with higher interest rates (e.g., Bester 1985). These theories predict a tradeoff in credit negotiations between the interest rate and other credit terms if the bank offers its menu sequentially to the firm. Panel B of Table III tests this prediction and presents the empirical distribution of the tradeoffs between the interest rate and the other credit terms. Remarkably, in 95 percent of the agreements on a credit facility there are no credit term changes or only interest changes. In addition, the table also does not provide evidence for a clear tradeoff between credit terms in the negotiations in which the interest rate changes in combination with another credit term (for example a lower interest rate and more collateral). These two findings suggests that tradeoff theories do not form an important explanation for the observed credit term changes after the first offer.

Figure 1 shows the distribution of the interest rate decreases conditional on an interest decrease. Loan officers most frequently make a concessions of 50 basis points, followed by concessions of 25 basis points. Panel C of Table III presents the empirical distribution of the interest changes. The table investigate the relation between the heights of the first offer and the distribution of the interest changes and shows that the magnitude of the interest decreases are larger for the highest decile of the first offers than the lowest decile. This suggest that loan officer which set a high first offer have a larger negotiation room which enables to make in larger interest concessions.

3. The effect of lending relationships and firm opaqueness

Do lending relationships and firm opaqueness affect bargaining behavior? This section investigates how these two factors affect the setting of the first offer of the bank, the

---

that they consider renegotiations of existing facilities and compares the credit terms between the origination of the syndicated loan and the first renegotiations of the contract, while this paper only examines new facilities and compares the credit term changes between the first offer and the agreement.

likelihood of an interest decrease and the likelihood that the firm and the bank reach an agreement.

3.1 The first offer

Loan officers sets the first offer based on their analysis of the creditworthiness of the firm and their information about the bargaining power of the firm. This section tests the prediction that relationships and small and young firms have less bargaining power and receive a first offer with a higher interest rate. The advantage of analyzing the first offer of the bank instead of the outcomes of the negotiations is that it also include the offers which do not reach an agreement with the bank which reduces selection concerns. To test the impact of relationships and opaqueness on the first offer, the paper estimates the following specification:

$$\textit{first offer interest rate}_i = \beta_1\, \textit{relationship}_i + \beta_2\, \textit{opaqueness}_i + \beta_2\, X_i + \varepsilon_i\,, \qquad (1)$$

where *first offer interest rate*$_i$ is the all-in interest rate of the facility in the first offer of the bank to the firm, *relationship*$_i$ is a vector which includes the relationship variables *relationship, relationship length, debt from other banks, good reputation* and three *customer risk grade dummies*, *opaqueness* $_i$ is a vector which includes *firm size* and three *firm age* dummies, X_i is a vector with control variables to control for differences in the credit terms of the facilities and observable credit risk. Each credit offer could include multiple facilities and since the errors of facilities within the same credit offer could be correlated, the paper clusters the standard errors at the credit offer level.

To capture the strength of the relationship the paper uses dummy *relationship* which takes the value of one if the firm has an existing relationship with the bank, the logarithm of the *relationship length* in years and a dummy *debt from other banks* which takes the value of one if the firm has debt of other banks. Over the lending relationship the bank collects private information about the creditworthiness of the firm. To capture this private information the paper includes a dummy *reputation* which takes the value of one if the loan officer indicate in the credit application that the firm kept past agreements with the bank and the bank has in general a good experience with the firm. In addition, specification includes three dummies which measure whether the firm has a good, medium or bad customer risk grade. The customer risk grade is a rating based on the credit line usage and transaction account behavior of the firm. Mester, Nakamura, and Renault (2007) and Norden and Weber (2010) show that this information is a good predictor of defaults in addition to available public information and is used in lending decisions. The paper uses *firm size*, measured as the logarithm of the total assets of the firm and three *firm age* dummies to capture the opaqueness of the firm. Young and smaller firms are more opaque because of the shorter track record and often unaudited financial records and Hadlock and Pierce (2010) show that firm size and age are an important indicator of financial constraints. The first offer interest rate contains bank rents, the credit risk premium and the funding costs of the bank. To control for the credit risk premium and the funding costs of the bank the specification includes the non-interest credit terms of the first offer, such as the collateral ration, the facility size, the maturity of the facility and three dummies which take the value of one if the facility is a credit line, has a fixed interest rate and include installment. In addition, the specification includes the internal funding costs of the facility, 12 credit rating dummies, 11 industry dummies, 12 year month dummies, and 80 branch dummies.

Table IV presents the results of the estimation of the first offer interest rate. The first column tests hypothesis H.1. that relationships receive a higher first offer than other firms. The results in column (1) show that the offer to firms with a relationship is 20 basis points higher than similar new clients of the bank which apply for a similar credit facility. The paper finds similar results when using the alternative relationship measure, relationship length, which are presented in column (2). The interest rate on the first offer of firms with debt from other banks is slightly higher than the offer of firms without other lending relationships, but this result is not robust over different specifications. In addition, young and small firms receive a higher first offer interest rate. The specification includes various controls to account for differences in credit risk, such as the first offer non-interest credit terms of the facilities and, industry dummies, credit rating dummies and year month dummies. To address the concern that relationship characteristics, firm size and age are correlated with unobserved credit risk the paper estimates in the next section the impact of relationship and opaqueness on the interest changes.

Hypothesis H.2. predicts that banks use private information to discriminate between good and bad firms which are observably equivalent for other banks. To test this prediction the paper includes two measures which capture information about the creditworthiness of the relationships which the bank collects over the course of the lending relationship, the reputation of the firm and the customer risk grade based on the credit line usage and transaction account activity of the firm. Firms with a good reputation receive a 27 basis points lower first offer and firms with a bad customer risk grade receive a 24 basis points higher first offer. These results show that the bank uses this information to discriminate between “good” and “bad” firms which is in line with informational capture theories.

An alternative explanation for the results is differences in the bargaining ability of the loan officer. If better more experienced loan officers negotiate with relationships, not the informational advantage of the bank but differences in the ability of the loan officers explain why relationships receive a higher offer. To test whether loan officer bargaining ability drives the results the paper includes loan officer fixed effects. The coefficient on relationships decreases which suggests that loan officer fixed effects are correlated with the relationship variables, but the main result that relationships receive a higher first offer does not change.

3.2. The likelihood of an interest decrease

The previous section shows that relationships, small and young firms receive a higher first offer than otherwise similar firms. One concern is that these variables are correlated with unobserved credit risk which implies that they are riskier than other firms. To address this concern, this section estimates the likelihood of an interest decrease. Since credit negotiations take place in a relative short period of 11 days, the underlying creditworthiness of small firms is unlikely to change.

The paper estimates the likelihood of an interest decrease with the following probit model:

$$Pr(interest\ decrease_i) = \Phi\ (\beta_1\ relationship_i + \beta_2\ opaqueness + \beta_2\ X_i), \qquad (2)$$

where $Pr(interest\ decrease_i)$ is the probability of an interest decrease ($\Delta interest\ spread < 0$), $\Phi(.)$ is the standard normal cumulative distribution function, $relationship_i$ is a vector which includes the relationship variables *relationship, relationship length, debt from other banks, good reputation* and three *customer risk grate dummies, opaqueness*$_i$ is a vector which includes *firm size* and three *firm age* dummies, X_i is a vector with control variables to control for differences in the credit terms of first offer and observable credit risk. The control variables include the *first offer interest rate* which determines the initial size of the bank rents and therefore the room to negotiate. In addition, the specification includes 13 industry fixed effects, 85 branch fixed effects and 11 year-quarter dummies. Each credit offer could include multiple facilities and since the errors of facilities within the same credit offer could be correlated, the paper clusters the standard errors at the credit offer level.

Table V presents the results of the estimates of the likelihood of an interest decrease. The paper firstly tests hypothesis H.3., which predicts that relationships are less likely to negotiate an interest decrease. Column (1) shows that the likelihood that relationships negotiate an interest decrease is 3.2 percent lower than otherwise similar firms. Column (2) shows that firms with a longer relationship are also less likely to negotiate an interest decrease. These findings are consistent with the findings in Table III that relationships receive a higher interest rate in the first offer. The bank is less likely to negotiate with firms with debt from other banks. Since the likelihood and magnitude of the winner's curse is higher in these situations, the bank should make less aggressive concessions in the negotiations. The paper also finds that larger and older firms are more likely to negotiate. Firms which are more than 8 years in business are 3 percentage points more likely to negotiate an interest decrease. Although the existing literature (e.g. Petersen and Rajan, 1994) documents that larger and older firms have a lower cost of credit, but in cross sectional studies it is difficult to disentangle whether these firms are less risky or whether banks extract less rents from them. Since negotiations take place over a short period of 12 days the actual credit risk of small firms is not likely to change. The results therefore show that banks have less bargaining power when negotiating with larger and older firms. These firms are more transparent and well known in the credit market and therefore are more likely to have outside options.

Information capture theories that relationship banks make an offer to “bad” firms which equals their marginal lending costs and extract an informational rent from “good” firms. Since the relationship bank does not extract profit from bad borrowers, they could not make concession to them in credit negotiations. Therefore, hypothesis H.4. predicts that bank only negotiate with “good” firms. The paper tests this hypothesis in column (3) by including the private information measures. The results show that the likelihood of an interest decreases reduces with 4.4 percentage points if the firm has a bad customer risk grade, which is in line with hypothesis H.4.

Section 2 discussed three alternative explanations why banks make concessions in credit negotiations; new information which changes the banks estimate of the creditworthiness, trade-offs between credit terms and the bargaining ability of the loan officer. To test whether learning could explain the interest decreases, the paper includes the credit rating changes between the first offer and the agreement in the specification. If the bank learns new information about the firm, the bank is likely to update the firm’s credit rating.[16] In 2.2 percent of the agreement the credit rating of the first offer is different from the credit rating of the agreement and in 1.2 percent of the agreements the credit rating decreases. Column (4) shows that the coefficient on the credit term changes is negative, but insignificant. Therefore, it is unlikely that new information about the firm which results in credit term changes drives the results.

The descriptive statistics in Table III show that only a small share of the negotiations result in an agreement with changes in the interest rate in combination with other credit terms. To consider the effect of other credit term changes on the likelihood of

[16] The bank has incentives to update the credit rating because credit ratings are used for regulatory purposes to determine the risk weight of the loan portfolio under the Internal Ratings-Based Approach of Basel III. A better portfolio quality results in a lower risk weight and as a consequence a lower capital requirement.

an interest decrease, the paper includes the changes in the new credit volume, collateral value and maturity and non-lending product sales as explanatory variables in column (5). Column (5) shows that changes in the facility size increase the likelihood of an interest decrease, but changes in the collateral ration, maturity and covenants do not explain interest decreases. In 11 percent of the agreements the funding cost of the bank change between the first offer and the agreement. Column (5) shows that these funding cost changes are an important explanatory factor of interest decreases. However, they do not affect the main result that relationships, smaller and younger firms are less likely to negotiate. The firm and the bank could also negotiate about non-lending products and demand a lower interest rate in return for non-lending product sales. Santikian (2012) finds that non-lending products are an important determinant of credit terms and increase the bargaining power of the firm. The results of the specification in column (6) include a cross selling dummy which takes the value of one if the firm purchase non-lending products and zero otherwise. The coefficient on the cross selling dummy is positive and significant and shows that firms which purchase non-lending products are 2.1 percentage points more likely to negotiate a lower interest rate. The change in the cross selling dummy between the first offer and the agreement does not predict the likelihood of a negotiation.[17] Although tradeoffs between the sales of non-lending products and the interest rate could explain part of the interest decreases, they do not affect the main results.[18]

3.3 The likelihood of an interest decrease, sample selection

The bargaining power of a firm is determined by the ability of the firm to generate competitive outside options. Instead of accepting the offer of the bank, firms with bargaining power could decide to accept an offer of another bank. The previous section estimates the likelihood of an interest decrease, conditional on reaching an agreement with the bank. A selection problem arises if firms that reach an agreement differ in

[17] Using more detailed data on cross selling for a subsample of the agreements shows that the number of non-lending products predicts the likelihood of a negotiation, but does not affect the result that relationships are less likely to negotiate an interest decrease.

[18] Also the inclusion of all explanatory variables in column (4) to (6) does not change the main results.

important unobserved ways from firm which do not reach an agreement with the bank. To address these selection concern this paper uses a Heckman selection model to jointly estimate the likelihood of an agreement and the likelihood of negotiating an interest rate. In addition, the selection model enables to test hypothesis H.5 that banks are more likely to reach an agreement with relationships and that this likelihood is higher if the bank has positive private information about the firm.

The firm's choice to reach an agreement with the bank depends on firm characteristics, relationship characteristics and the characteristics of the first offer of the bank. Let I_i be the observable characteristics that determine that the firm and the bank reach an agreement; for instance, the firm's credit rating, its total assets and the first offer interest rate. Agreements are observable and recorded by the variable, $agreement_i$, which describes the following selection equation:

$$agreement_i = \begin{cases} 1 & \text{if the firm reaches an agreement with the bank: } \gamma' I_i \geq \varepsilon_i \\ 0 & \text{if the firm does not reach an agreement with the bank: } \gamma' I_i < \varepsilon_i, \end{cases} \quad (3)$$

where ε_i are the characteristics of negotiation *i* which are unobservable but affect whether the negotiation results in an agreement and might also affect the firm's choice to negotiate. The instrument used to estimate the selection equation is the application time, which is the time between the credit application and the first offer. The motivation for this instrument comes from discussions with loan officers who complain about bureaucratic delays in the application process, for example due to illness of the supporting staff. The application time is a measure how quick the bank could make a first offer and if there are delays in the application, there is a chance that the firm already accepted a competing offer. The application time affects the decision of the firm to accept the offer because a long application time increases the probability that a firm accepted an offer from another bank, but does not affect the interest rate.[19] The average application

[19] The application time might be correlated with credit risk because the approval of risky offers might take longer or because the bank processes applications of firms with possible outside options faster. To address

time for all firms which receive a first offer is 16 days and has a standard deviation of 17 days. The following regression equation models the likelihood of an interest decrease:

$$Pr(interest\ decrease_i) = \Phi\ (\beta_1\ relationship_i + \beta_2\ opaqueness + \beta_3\ X_i), \qquad (4)$$

where *interest decrease*$_i$ is a dummy which takes the value of one if the interest rate decreases over the negotiation and zero otherwise, Φ is the standard normal cumulative distribution function and the β's are the unknown parameters. The specification is similar to equation (2). The selection equation (3) and the regression equation (4) are jointly estimated with maximum likelihood.

Table VI reports the results of the selection model and shows that the coefficient on the instrument, the *application time*, is negative and significant as predicted. A one standard deviation increase in the application time reduces the likelihood of an agreement with 4 percentage points, which shows that the application time is an important determinant of agreements. The test statistic reported at the bottom of the table is the result of the Wald test which tests the hypothesis that the error terms of the selection and regression equation are uncorrelated (Rho = 0). The results show that the null hypothesis of independent errors could not be rejected, which implies that the error terms of the selection equation and the regression equation are not correlated. This implies that the results of the previous section are not driven by unobserved firm characteristics correlated with one of the explanatory variables.

Apart from the correction for a potential selection bias, the result of the selection equation could provide additional evidence on the determinants of bargaining power. Firm bargaining power should not only affect the likelihood of a negotiation, but also the likelihood that the firm reaches an agreement with the bank. Firms with more outside options, and therefore more bargaining power, are less likely to reach an agreement than firms with just one offer. The results in column (1) and (2) show that most of the coefficients on the variables in the selection and regression equation have opposite signs.

---

this concern the selection equation includes direct measures of credit risk and outside options, such as the credit rating and firm size.

For example, relationships, as predicted by H.5., are more likely to reach an agreement with the bank and less likely to negotiate an interest decrease. Both findings provide evidence that relationships have less bargaining power in the credit market. Similarly, smaller and younger firms are more likely to reach an agreements and less likely to negotiate an interest decrease. Firms with debt from other banks are less likely to reach an agreement, because they are more likely to have an outside option of the other bank. The potential winner's curse could explain why these firms are less likely to negotiate an interest decrease with the bank.

One empirical prediction of the "informational capture" theories is that "bad" firms are more likely to switch to another bank than "good" firms. The evidence presented in Table VI is mixed. The paper finds that firms with a good reputation are more likely to reach an agreement. If other competing banks could not observe the reputation of the firm, the relationship bank could exploit offer them better terms than an outside bank, which increases the likelihood that the firm reaches an agreement with the bank. However, firms with a bad customer risk grade based on their credit line usage and transaction account behavior are more likely to reach an agreement. Informational capture theories predict that in particular bad firms are more likely to switch. The bad information captured by this measure includes limit violations and a decreasing turnover on the current account of the firm. One explanation for this finding is that some of this information is observable by outside banks, for example if an outside bank asks for a half year financial report. If these firm do not receive outside offers (an assumption of the informational capture theories) they have to accept the offer of their relationship bank.

4. The effect of negotiations on the agreed interest rate

A firm possesses bargaining power if the firm can affect the bargaining outcome in a way desirable for him. If the bargaining measures employed in the main sections of this paper actually capture the bargaining power of the firms, negotiating firms should pay a lower interest rate than similar firms which accept the first offer. The main goal of this section is to test this hypothesis. Alternatively, loan officers could anticipate on the negotiation by raising the first offer interest rate above the desired interest rate and make concessions to finally and up at the desired interest rate. In this scenario, negotiating firms pay the same interest rate as similar firms which accept the first offer of the bank. The paper estimates the following specification to examine the impact of a negotiation on the agreed interest rate:

$$agreed\ interest\ rate_i = \beta_1 interest\ decrease_i + \beta_2 X_i + \varepsilon_i, \tag{5}$$

where $Agreed\ interest\ rate_i$ is the all-in interest rate of the agreement, $interest\ decrease_i$is a dummy which takes the value of one if the interest rate decreases over the negotiation ($\Delta interest\ rate < 0$) and X_i is a matrix of covariates to control for differences in credit risk across the negotiations. The matrix of control variables includes firm characteristics (firm size, profitability, leverage, new credit demand and the demand for working capital) and relationship characteristics (lending relationship, debt from other banks, non-lending products). In addition, the specification includes 13 credit rating fixed effects, 13 industry fixed effects, 85 branch fixed effects and 11 year-quarter dummies. Each credit offer could include multiple facilities and since the errors of facilities within the same credit offer could be correlated, the paper clusters the standard errors at the credit offer level.

Table VII shows in column (1) that negotiating firms pay an interest rate which is 33 basis points lower than similar firms which accept the first offer of the bank, which is 8 percent of the average first offer interest rate. Conversations with loan officers tell that “a quarter” (25 basis points) is a common discount they give in negotiations. According to one loan officer “less than a quarter does not move a firm and more than a quarter is a too large discount”. Therefore, the estimated magnitude of the discount is economically meaningful. In addition, the result shows that negotiating firms actually improve the terms of their credit offer, which is in line with the interpretation that interest changes reflect firm bargaining power.[20] To test whether larger concessions also result in a lower

[20] An alternative method to compare negotiating firms with firms which accept the first offer is to use a non-parametric matching method. By matching firms on observable characteristics one could compare the agreed interest rate of similar firms which negotiated and interest decrease or accepted the first offer of the bank. The results of non-parametric matching method are similar to the results of the linear model used in this section.

interest rate column (2) includes the change in the interest rate $\Delta interest\ rate$ and the square of the interest rate change to test for non-linear effects. The results show that for each interest decrease of 100 basis points the firms receives a 49 basis points discount compared with firms which accept the first offer of the bank. This suggests that negotiating firms receive a high first offer than similar firms which directly accept the first offer, but at the end, after negotiating are still better off than firms which accept the first offer. The square of the interest rate changes variable is positive a significant, which suggest that firms with a larger interest change receive a smaller discount.

Does the negotiated discount differ across firms? To answer this question the paper tests whether relationships, firms with debt from outside banks, large firms and older firms receive a larger discount after a negotiation by interacting these variables with the interest decrease variable. Column (3) presents the results and shows that firms with debt from other banks receive a larger discount and larger firm receive a small er discount. One explanation for the first result is that firms only want to switch when the discount is interactive enough for them and compensates sufficient for the fixed switching costs. One explanation why larger firms receive a smaller discount is that their first is already more competitive which reduces the negotiation room of the bank. This explanation is consistent with the findings in Table IV.

Credit negotiations determine the division of the surplus between the firm and the bank. The division of the surplus might also depend on the bargaining abilities of the loan officer. This would imply that the bargaining power measure does not capture firm, but loan officer bargaining power. The inclusion of loan officer fixed effect enables to test this hypothesis. If the interest decrease variable is correlated with unobserved loan officer characteristics, its coefficient would decrease in magnitude or become even insignificant after the inclusion of loan officer fixed effects. Column (4) shows that the inclusion of loan officer fixed effect increases the R-squared of the interest model from 77.1 percent to 78.4 percent. Since the specification already controls for differences in firm characteristics, this results suggest that unobserved loan officer characteristics, such as bargaining ability, affect the outcomes of the negotiation. However, the magnitude of the interest decrease coefficient only slightly changes after the inclusion of loan officer fixed effects. This shows that firm bargaining power and not the bargaining ability of the loan officer drives the result.

5. Conclusions

This is the first paper which studies the negotiation process and bargaining behavior in the small business credit market. The paper uses a unique hand collected data set of 18,591 credit negotiations between small firms and one large commercial bank in the Netherlands during the period January 2008 - December 2010 which include detailed information about the negotiation process. Studying the negotiation process provides novel evidence on the design of credit contracts and the distribution of bargaining power between firms and banks. For example, this paper shows that in a typical credit negotiation the firm and the bank first set the collateral requirements, which show the importance of collateral in the provision of credit to small firms. The paper also shows that relationships and opaque firms have less bargaining power in negotiations and banks use their privately collected information about their relationships to discriminate between “good” and “bad” which are observably equivalent to other banks which do not lend to these firms. Negotiating firms pay a 33 basis points lower interest rate than otherwise similar firms which accept the first offer.

Figure 1: The distribution of interest decreases

Figure 1 shows the distribution of the interest decreases in basis points, conditional on an interest decrease.

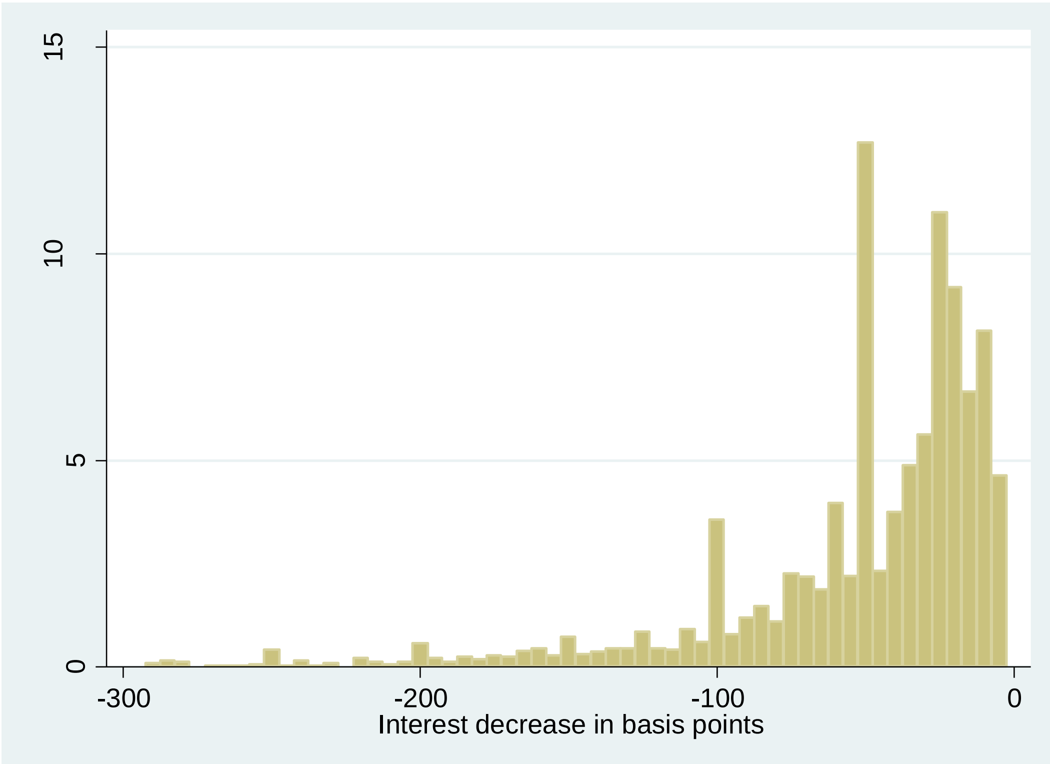


Table I: Summary statistics

Table I presents the summary statistics of the firm characteristics, the relationship characteristics and the credit demand and provides the mean, median and standard deviation (SD) for all 18,591 credit negotiations. The definitions of the variables can be found in Appendix I.

	Mean	Median	SD
Firm characteristics			
Total assets (€1000)	607	341	1,965
Firm age < 3 years	0.05	0	0.23
Firm age 3-8 years	0.19	0	0.39
Firm age > 8 years	0.59	1	0.49
Turnover (€1000)	913	356	3,849
Corporation (0 – 1)	0.39	0	0.49
Credit rating (1 – 7)	3.9	4.0	0.76
Relationship characteristics			
Relationship (0/1)	0.66	1	0.47
Relationship length (years)	6.7	2.5	8.63
Debt from other banks (0/1)	0.24	0	0.43
Good reputation	0.62	1	0.49
Good customer risk grade	0.30	0	0.46
Medium customer risk grade	0.05	0	0.22
Bad customer risk grade	0.03	0	0.17
Credit demand			
Credit demand (thousand euro)	227	145	251
Real estate (%)	0.33	0	0.42
Corporate investment (%)	0.20	0	0.33
Working capital (%)	0.38	0.16	0.44
Repayment debt from other banks (%)	0.06	0	0.21
Other (%)	0.05	0	0.18

Table II: The setting of the credit terms of the first offer

Table II presents the summary statistics of the setting of the credit terms of the first offer. Panel A presents the time to the last update of the collateral requirements (Collateral), the non-interest credit terms (e.g. size and maturity) of the individual credit lines and term loans (Facilities) and the interest rates and fees of the credit offer. The time to the last update is the time in days between the first meeting with the firm and the last update of the credit contract. Panel B presents the distribution of the order in which the credit terms are set during the negotiations, based on the last update of the credit term.

Panel A: Time between the first meeting with the firm and the last update

	Time to the last update (days)	
Credit term	Mean	Median
Collateral	19.8	10.9
Facilities	21.1	12.2
Pricing	24.5	14.8

Panel B: The order of the last update of the credit terms of the first offer

			All	No relationship	Relationship
First term	Second term	Last term	%	%	%
Collateral	Facilities	Pricing	86.7	62.7	97.7
Facilities	Collateral	Pricing	13.2	37.2	2.2
Other orders			0.1	0.1	0.1

Table III: Negotiation summary statistics

Table III presents the negotiation summary statistics. Panel A presents the summary statistics of the 18,591 first offers of the bank, which include 27,459 new facilities. The table contains the credit terms of the facilities of the first offer and provides their mean, median and standard deviation. In addition, the table provides the mean credit terms of the agreements and the percentage of the agreement containing positive and negative changes of the specific credit term. Panel B presents the trade-offs between the interest rate and other credit terms. Panel C presents the distribution of the interest changes for all agreements and for the highest and lowest decile of the first offer interest rate.

Panel A: Summary statistics of the first offer and the credit term changes

		First offer			Agreements		
Variable name		Mean	Median	SD	Mean	Credit term increase (%)	Credit term decrease (%)
Credit line	(0/1)	0.37	0	0.48	0.37		
Facility size	€1000	137	100	137	133	1.1	1.0
Collateral ratio	%	0.81	0.85	0.43	0.81	1.7	1.9
Maturity	years	6.7	5	7.15	6.5	0.5	0.5
Covenants	#	0.40	0	0.61	0.39	0.1	0.2
Interest rate	bps	621	630	235	615	3.6	15.1
Negotiation time	days				12.97		
Observations		27,459 (100%)			22,071 (80%)		

Panel B: Trade-offs between the interest rate and other credit terms (in percentages of the total number of agreements)

	All agreements	Agreements with:									
		No non-credit	Facility size		Collateral value		Maturity		Covenant		
		term changes	increase	decrease	increase	decrease	Increase	decrease	increase	decrease
No interest change	81.3	79.9	0.2	0.2	0.6	0.6	0.1	0.1	0.0	0.1
Interest increase	3.6	2.5	0.3	0.4	0.4	0.4	0.2	0.1	0.0	0.0
Interest decrease	15.1	12.7	0.7	0.4	0.7	0.9	0.2	0.3	0.1	0.2
Total	100	95.1	1.1	1.0	1.7	1.9	0.5	0.5	0.1	0.2

Panel C: The first offer and the likelihood of interest rate changes

	Interest rate change (bps):												
	<-125	-125	-100	-75	-50	-25	0	25	50	75	100	125	125<
All agreements	1.6	0.4	1.0	1.3	3.7	5.5	83.8	0.7	1.2	0.3	0.2	0.2	0.3
First offer interest rate (bps)													
Highest decile (>500 bps)	5.4	0.9	2.1	1.8	3.0	1.8	83.5	0.4	0.2	0.2	0.1	0.1	0.4
Lowest decile (<100 bps)	0	0	0.4	0.6	3.22	8.5	82.4	1.2	2.6	0.1	0.1	0.1	0.6

Table IV: The first offer interest rate

$$First\ offer\ interest\ rate_i = \beta_1 Relationship_i + \beta_2 Opaque_i + \beta_3 X_i + \varepsilon_i$$

Table IV presents the results from a regression with f*irst offer interest rate$_i$* as dependent variable. The sample includes the 27,459 facilities of the 18,591 first offers. The *first offer non-interest credit terms* include the facility size, the collateral ratio, maturity and a credit line, fixed interest rate and installment dummy. The definitions of the independent variables can be found in Appendix I. In addition, the baseline specification includes 13 industry dummies and 55 region dummies and 11 year – quarter dummies. The dependent variable is estimated with OLS. Statistical significance at 10%, 5% and 1% levels is denoted by *, **, *** respectively . Standard errors are robust and clustered at credit offer level.

	(1)	(2)	(3)	(4)
Relationship characteristics				
Relationship	20.30***		37.26***	26.99***
	(2.28)		(4.68)	(4.95)
Relationship length		5.45***		
		(1.39)		
Debt from other banks	3.10***	-2.61	2.60***	3.49*
	(1.97)	(1.81)	(1.95)	(2.02)
Good reputation			-27.34***	-17.80***
			(4.28)	(4.52)
Good customer risk grade			12.97***	10.49***
			(2.75)	(2.90)
Medium customer risk grade			25.28***	23.68
			(4.18)	(4.37)
Bad customer risk grade			23.65***	24.44***
			(5.46)	(5.61)
Opaqueness				
Firm size	-27.27***	-26.89***	-27.21***	-25.59***
	(0.90)	(0.90)	(0.09)	(0.97)
Firm age 1-3 years	-13.11***	-1.17	-12.98***	-13.52***
	(4.86)	(4.58)	(4.85)	(4.94)
Firm age 4-8 years	-24.49***	-11.45***	-23.54***	-24.94***
	(3.54)	(3.10)	(3.54)	(3.67)
Firm age > 8 years	-25.94***	-13.76***	-24.47***	-23.68***
	(3.28)	(2.83)	(3.30)	(3.44)
Loan officer fixed effects				YES
First offer non-interest credit terms	YES	YES	YES	YES
Industry, credit rating FE	YES	YES	YES	YES
Branch and year - quarter FE	YES	YES	YES	YES
Observations	27,459	27,459	27,459	27,459
R^2	0.762	0.762	0.763	0.794

Table V: The likelihood of an interest decrease

$$\Pr(\textit{interest decrease}_i\ ) = \Phi\ (\beta_1 \textit{Relationship}_i + \beta_2 \textit{Opaque}_i\ + \beta_3 X_i)$$

Table V presents the results from a regression with *interest decrease* as dependent variable. The sample includes the 22,071 facilities of the 15,376 credit agreements. The *first offer credit terms* include the first offer interest rate, the facility size, the collateral ratio, maturity and a credit line, fixed interest rate and installment dummy. The definitions of the independent variables can be found in Appendix I. In addition, the baseline specification includes 13 industry dummies and 55 region dummies and 11 year – quarter dummies. The dependent variable is estimated with a probit model and the marginal effects are reported in percentage points. Statistical significance at 10%, 5% and 1% levels is denoted by *, **,*** respectively . Standard errors are robust and clustered at credit offer level.

	(1)	(2)	(3)	(4)	(5)	(6)
Relationship characteristics						
Relationship	-3.22***		-4.58***	-3.21***	-3.11***	-3.09***
	(0.91)		(1.74)	(0.91)	(0.91)	(0.91)
Relationship length		-0.87***				
		(0.32)				
Debt from other banks	-1.43**	-1.03	-1.39*	-1.46**	-1.51**	-1.42**
	(0.72)	(0.71)	(0.73)	(0.73)	(0.72)	(0.072)
Good reputation			1.96			
			(1.30)			
Good customer risk grade			-0.08			
			(0.86)			
Medium customer risk grade			-3.02**			
			(0.03)			
Bad customer risk grade			-4.35***			
			(1.27)			
Opaqueness						
Firm size	1.05***	1.01***	1.11***	1.06***	0.89***	1.06***
	(0.30)	(0.30)	(0.30)	(0.30)	(0.30)	(0.30)
Firm age 1-3 years	1.98	0.27	1.91	1.97	2.07	1.96
	(1.66)	(1.45)	(1.66)	(1.66)	(1.66)	(1.66)
Firm age 4-8 years	5.19***	3.33***	5.10***	5.22***	5.12***	5.20***
	(0.14)	(1.17)	(1.41)	(0.14)	(1.40)	(1.41)
Firm age > 8 years	3.14***	1.78*	3.12***	3.17***	3.11***	2.14***
	(1.17)	(1.05)	(1.17)	(1.17)	(1.17)	(0.77)

Table V (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Credit rating and credit term changes						
ΔCredit rating				-4.50		
				(3.58)		
ΔFacility size					0.05***	
					(0.01)	
ΔCollateral ratio					1.47	
					(6.52)	
ΔMaturity					-0.53	
					(0.41)	
ΔCovenants					-6.345	
					(4.37)	
ΔFunding costs					-0.28***	
					(0.03)	
Cross selling						
Cross selling						2.11***
						(0.77)
ΔCross selling						0.97
						(0.21)
First offer credit terms	YES	YES	YES	YES	YES	YES
Industry, credit rating, branch and year - quarter FE	YES	YES	YES	YES	YES	YES
Observations	22,122	22,122	22,122	22,122	22,122	22,122
Pseudo-R^2	0.056	0.055	0.058	0.057	0.077	0.057

Table VI : The likelihood of an interest decrease, sample selection correction

$$agreement_i = \begin{cases} 1 & \text{if the firm reaches an agreement with the bank: } \gamma' I_i \geq \varepsilon_i \\ 0 & \text{if the firm does not reach an agreement with the bank: } \gamma' I_i < \varepsilon_i, \end{cases}$$

$$\Pr(interest\ decrease_i) = \Phi\ (\beta_1 Relationship_i + \beta_2 Opaque_i + \beta_3 X_i)$$

Table VI presents the results from the estimation of the likelihood of an *interest decrease* with a correction for the negotiations which do not result in an agreement, which might result in a sample-selection bias. To address this potential sample selection problem the paper estimates a Heckman selection model. The selection equation includes the *application time* as the identifying instrument, which is not included in the main estimation. The *first offer credit terms* include the first offer interest rate, the facility size, the collateral ratio, maturity and a credit line, fixed interest rate and installment dummy. The definitions of the independent variables can be found in Appendix I. In addition, the baseline specification includes 13 industry dummies and 55 region dummies and 11 year – quarter dummies. Both the selection and regression equation are estimated by maximum likelihood estimation and the marginal effects are reported in percentage points. Rho is the correlation between the error terms of the selection and regression equation. The Wald test of independent equations tests the hypothesis that rho equals to zero. A significant Chi-square test statistics rejects the hypothesis that the error terms are uncorrelated and justifies the use of the Heckman selection equation. Statistical significance at 10%, 5% and 1% levels is denoted by *, **, *** respectively. Standard errors are robust.

	(1)	(2)
Equation:	Selection	Regression
Dependent variable:	Agreement	Interest decrease
Relationship characteristics		
Relationship	7.25***	-4.91***
	(1.16)	(0.015)
Debt from other banks	-1.38***	-1.62***
	(0.56)	(0.64)
Good reputation	4.41***	1.85
	(1.11)	(1.13)
Good customer risk grade	0.99*	1.24**
	(0.57)	(0.61)
Medium customer risk grade	7.64***	-3.67***
	(1.24)	(1.34)
Bad customer risk grade	11.00***	-4.00***
	(1.86)	(1.34)
Opaqueness		
Firm size	-3.54***	1.26***
	(0.22)	(2.63)
Firm age 1-3 years	-7.00***	2.82**
	(1.19)	(1.42)
Firm age 4-8 years	-10.76***	6.03***
	(0.86)	(1.26)
Firm age > 8 years	-8.52***	4.00***
	(0.82)	(1.13)

Table VI (Continued)

Instrument		
Application time	-1.08***	
	(0.21)	
First offer credit terms		
Industry, credit rating, branch and year - quarter FE	Yes	Yes
Uncensored observations	27,459	
Censored observations	22,071	
Rho	-0.013	
Wald test of independent equations (Rho = 0)	X^2 =0.01	

Table VII: The effect of negotiations on the credit agreement

$$Agreed\ interest\ rate_i = \beta_1 Interest\ decrease_i + \beta_2 X_i + \varepsilon_i$$

Table VII presents the results from a regression with the *agreed interest rate* as dependent variable. The sample includes the 22,071 facilities of the 15,376 credit agreements. The *firm characteristics* include the firm size and the three firm age dummies. The *relationship characteristics* include the relationship and debt from other banks dummies. The *agreed non-interest credit terms* include the facility size, the collateral ratio, maturity and a credit line, fixed interest rate and installment dummy. The definitions of the independent variables can be found in Appendix I. The dependent variable is estimated with OLS. Statistical significance at 10%, 5% and 1% levels is denoted by *, **, *** respectively . Standard errors are robust and clustered at credit offer level.

	(1)	(2)	(3)	(4)
Interest decrease	-32.78***		-68.02***	-54.32***
	(2.14)		(13.63)	(13.69)
Δ interest rate		0.49***		
		(0.02)		
Δ interest rate × Δ interest rate (10^{-3})		0.58***		
		(0.08)		
Interest decrease ×Relationship			-6.03	-11.52*
			(6.04)	(6.23)
Interest decrease × Debt from other banks			-13.30***	-13.59**
			(5.30)	(5.59)
Interest decrease × Firm size			6.34***	4.61**
			(2.31)	(2.29)
Interest decrease × Firm age 1-3 years			23.71	21.75
			(13.43)	(14.17)
Interest decrease × Firm age 4-8 years			4.58	5.85
			(9.67)	(9.76)
Interest decrease × Firm age > 8 years			6.39	7.27
			(8.94)	(9.00)
Firm characteristics	Yes	Yes	Yes	Yes
Relationship characteristics	Yes	Yes	Yes	Yes
Agreed non-interest credit terms	Yes	Yes	Yes	Yes
Industry, credit rating, branch and year -				Yes
quarter FE	Yes	Yes	Yes	
Loan officer FE				Yes
Observations	22,122	22,122	22,122	22,122
R^2	0.771	0.773	0.771	0.784

Appendix I: Variable definitions

Variable name	Definition
Dependent variables	
First offer interest rate	The first offer interest rate is the facility size weighted average interest rate of the credit agreement, in basis points.
Interest decrease	= 1 if the interest rate change between the first offer and the agreement is negative and 0 otherwise.
Agreed interest rate	The agreed interest rate is the facility size weighted average interest rate of the credit agreement, in basis points.
Default	= 1 if the firm defaults on its obligations within 12 months after the origination and 0 otherwise.
Independent variables	
Relationship	= 1 if the firm has an existing relationship with the bank and 0 otherwise.
Relationship length	The length of the relationship between the firm and the bank in years.
Debt from other banks	= 1 if the firm has debt from other banks and 0 otherwise.
Non-lending products	= 1 if the firm purchases non-lending products from the bank and 0 otherwise.
Good reputation	= 1 if the loan officer reports that the firm keeps past agreements there are good experiences with the firm and zero otherwise.
Good customer risk grade	= 1 if the customer risk grade, which is a credit rating based on the credit line usage and the transaction account behavior, equals 1 or 2 and 0 otherwise.
Medium customer risk grade	= 1 if the customer risk grade, which is a credit rating based on the credit line usage and the transaction account behavior, equals 3 and 0 otherwise.
Bad customer risk grade	= 1 if the customer risk grade, which is a credit rating based on the credit line usage and the transaction account behavior, equals 4, 5 or 6 and 0 otherwise.
Total assets	Total assets from the latest annual report, in thousand euro.
Firm age 1-3 years	= 1 if the firm age is between 1 and 3 years and 0 otherwise.
Firm age 4-8 years	= 1 if the firm age is between 4 and 8 years and 0 otherwise.
Firm age > 8 years	= 1 if the firm age is higher than 8 years.
Facility size	Size of the credit facility, in thousand euro.
Collateral ratio	Collateral value / total credit volume.
Maturity	The maturity of the facility, in years.
Credit line	= 1 if the facility is a credit line and 0 otherwise.
Fixed interest rate	= 1 if the facility has a fixed interest rate and 0 otherwise.
Installment	= 1 if the facility includes installment payments and 0 otherwise
Application time	The application time is the time between the day of the credit application and the day of the first offer, in days.
Other variables	
Employees	Number of employees of the firm, in full-time equivalents.
Profitability	EBIT / total assets.
Debt-to-assets ratio	Total liabilities / total assets.
New credit demand	New credit demand is the firm's demand for new loans and does not include the existing debt of the firm or renewals, in thousand euro.
Credit demand for fixed assets	Credit demand for fixed assets is the firm's credit demand for fixed assets as share of the new credit demand.
Credit demand for working capital	Credit demand for fixed assets is the firm's credit demand for working capital as share of the new credit demand.

III Is Loan Officer Discretion Advised When Viewing Soft Information?

Abstract

We show that the collection of soft information on the activities of small and medium sized enterprises and the exercising of loan officer discretion helps in monitoring these borrowers. We measure loan officer discretion as the deviations in granted loan amounts from the amounts stemming from the bank's own credit scoring model. Soft information guides discretion, and helps in predicting loan default even when controlling for all available public and private information. Loan officers use soft information when deciding on the loan amount that is being granted: A one standard deviation of more favourable soft information results in the granting of a 16 percent higher loan amount. Beyond using soft information, loan officer discretion *per se* neither improves nor deteriorates loan outcomes.

1. Introduction

Banks - and not investors in capital markets - typically finance small and medium sized enterprises (SMEs). Extant theory suggests banks are able monitors of these firms (e.g., Diamond (1984), Boot (2000)), and can impede firm risk-shifting during normal times and mitigate losses in case of default (Holmström and Tirole (1997)). Yet, despite this prominent role attributed to bank monitoring in the theoretical literature, surprisingly little hard evidence documents its existence, contours and importance.

Using a unique data set that contains detailed information on bank monitoring activities (through their loan officers) at the loan origination stage and during the course of the bank-firm lending relationship, we investigate how bank monitoring controls risk-shifting and loss-mitigation, and impacts loan-level outcomes, and firm-level risk and income for the bank. The level of detail present in our data set allows us to observe whether the bank anchors its loan granting and condition setting in quantifiable <u>hard</u> information (e.g., a firm's leverage ratio), <u>soft</u> information (e.g., a subjective impression of the managerial ability of the firm's owner), or <u>discretion</u> exercisable by its loan officers (e.g., the possibility for loan officers to grant more money to the firm than the bank's program software that uses hard and soft information inputs provided by the loan officer himself recommends)?[1]

It is well-known that hard information is a major determinant in many lending decisions. Soft information, however, may also play an important role in many of such decisions. Decisions on loans to SMEs for example are often based on the detailed knowledge about their operational environment. Relationship banks invest in obtaining proprietary customer-specific information by evaluating the customers through multiple interactions over time (Boot, 2000). Furthermore, loan officers often enjoy the authority in determining lending terms such as the loan size and the loan rate.

---

[1] Petersen (2004) defines <u>hard</u> information as information which is quantitative, easy to store and transmittable in impersonal ways, and which content is independent of the collection process. Soft information is subjective, difficult to quantify and often stored in text form. <u>Soft</u> information is collected personally and the decision maker is often the same person as the information collector. Shavell (2007) discusses the optimal <u>discretion</u> given to adjudicators in the application of rules.

Both soft information and loan officer discretion may be valuable as inputs at the loan origination stage and during monitoring (e.g., Stein, 2002). The contents of the employed soft information however is difficult to verify and may lead to related lending depending upon the loan officer's compensation scheme and the degree of competition (Heider and Inderst, 2011), while decisions to exert discretion may put a loan officer's reputational capital at stake. In our setting, the use of discretion by loan officers is easily verifiable by headquarters. We therefore address the question whether the use of soft information and the exercise of discretion by loan officers is valuable to a financial unit by studying if and how loans based upon soft information and discretion have more favorable outcomes than otherwise similar loans.

To address this question properly one needs access to proprietary bank data on loan initiations and monitoring over the course of a bank-firm relationship. Existing research focuses mainly on the role of soft information and discretion at the screening stage, when a bank accepts or rejects a loan application, and its effects on bank risk (e.g., Agarwal and Hauswald, 2010b, Grunert and Norden, 2012, Puri, Rocholl and Steffen, 2011, and Gropp, Gruendl and Guettler, 2013). Our paper contributes to this nascent important literature by studying the impact of direct measures of soft information and loan officer discretion on lending outcomes over the entire course of a bank-firm lending relationship.

That soft information about SMEs, i.e., in many cases its handful of direct owners, matters for loan outcomes is self-evident for retail bankers. Character (integrity, honesty) and capacity (management ability) are considered as the two most important categories among the so-called "5C's of credit",[2] and soft information is at least essential if not the only way to assess it. Discretion allows the loan officer to tailor the loan contract terms to the firm, such that firm performance is maximized.

We investigate how valuable soft information and loan officer discretion are in lending decisions. To this end, we use a hand-collected panel data set on the credit

[2] This is a long-established practice in the U.S. banking industry to assess the creditworthiness of a borrower by examining five categories. Capital, collateral and conditions (in industry and economy) are the remaining three categories (Collins, 1966). See also the discussion in Grunert and Norden (2011) for example.

approvals and monitoring activities of a SME lending division of a bank over a six-year period. In particular, we extract indicators of soft information and loan officer discretion from 'customer evaluation forms' a loan officer completes during the credit application and the (typically annual) loan monitoring cycle.[3]

First, we classify the information in these forms into public, private hard and (private) soft information. Soft information comprises information: i) that the loan officer collected via personal interaction, and ii) for which human cognition is required to convert it into actionable intelligence. We create an aggregate measure of soft information and argue that this measure of soft information is a good proxy for the actual soft information possessed by the loan officer. We employ this unique and direct measure of soft information to investigate how valuable it is in determining loan conditions, monitoring, and predicting outcomes such as loan defaults.

Second, we study the determinants of loan officer discretion and investigate how loan officer discretion affects lending outcomes. Our dataset provides a direct measure of loan officer discretion. In particular, at loan origination as well as during each monitoring cycle, the information from the 'customer evaluation form' is put into the bank's internal credit scoring model that yields a *Model Limit*. This model limit employs different types of information (i.e., public, private hard and soft information). However, the loan officer has the authority to deviate from the model limit and propose a larger or smaller maximum exposure relative to this model limit. We label the deviations from the model limit as "discretion" by the loan officer. A unique property of our analysis is that loan officer not only decide on accept/reject decisions (the extensive margin) but also on the maximum exposure (the intensive margin).

---

[3] Soft information is subjective and inherently difficult to quantify. The empirical literature up to now mostly resorts to indirect measures, such as the distance between bank and borrower, the presence of review notes by the loan officer (Agarwal and Hauswald, 2010a), the personal interaction between a bank and borrower, or the length of the bank-borrower relationship (see e.g., Berger, Miller, Petersen, Rajan, and Stein, 2005). Agarwal and Hauswald (2010b) regress an internal bank credit score on public information indicators and employ the residual as a proxy for soft information. Similarly, loan officer discretion is indirectly measured through the use of a heteroskedastic loan pricing model in Cerqueiro, Degryse and Ongena (2011).

With these direct measures of soft information and loan officer discretion, we first investigate whether loan officers employ soft information in their lending decisions in addition to the public and private hard information that is available, and whether it determines loan performance and size. We find that a worsening of the soft information by one standard deviation worse increases the probability of default by 5.5 percent. Soft information therefore significantly helps in predicting loan default, even after controlling for public and private hard information. While soft information is largely uncorrelated with public and private hard information, its economic relevancy in predicting defaults is of an equal magnitude as that of public information. This finding suggests that soft information is an important additional factor in the determination of the creditworthiness of a borrower above and beyond public and private hard information.

We further find that a one standard deviation more favorable soft information results in a 4 percent increase in discretion, i.e., the deviation from the model limit determined by the credit scoring model. Remarkably, public and private hard information do not explain discretion. The overall impact of a one standard deviation change of our measure of soft information results in a 16 percent change in loan size. We do not find evidence that loans based upon more loan officer discretion perform differently than loans based on the credit scoring model only.

In sum, we show that soft information is an important part of the information set used in determining the creditworthiness of a borrower and that soft information is economically at least as relevant as other information employed during monitoring and screening, i.e., public and private hard information. Discretion is driven by a loan officer's soft information about the firm. Furthermore, loan officers employ discretion to smoothen shocks resulting from changes in the application of the model limit. Although our soft information indicator explains discretion, we do not find that discretionary choices themselves improve lending outcomes.

Our results show that soft information and loan officer discretion are correlated with lending outcomes. Our results are further robust to reverse causality concerns as the insights also hold for firms in which the bank is only a small lender, i.e., when the firm maintains multiple bank-firm relationships.

The papers closest to ours are Puri, Rocholl and Steffen (2011) and Gropp, Gruendl and Guettler (2013) and Brown, Schaller, Westerfeld and Heusler (2012). The first paper also studies the role of soft information and discretion in accept/reject decisions. In particular, they investigate deviations from a commonly implemented credit scoring model across savings banks in accept/reject decisions. They call these deviations decided by loan officers 'discretion'. Soft information drives discretion mainly for customers without credit history, whereas hard information drives it for consumers with a credit history. Accepted loans based on discretion do not perform differently than loans accepted on the basis of the scoring model.

Gropp, Gruendl and Guettler (2013) investigate the use of discretion by relationship and transaction banks. Discretion is measured as the rating upgrades or downgrades by banks relative to a commonly implemented model and these are argued to be based on soft information. They find that firms self-select relationship banks depending on the quality of their soft information.

Brown, Schaller, Westerfeld and Heusler (2012) use the loan officers' adjustments of small firm credit ratings as measure of discretion. They show that loan officers use discretion to smooth credit ratings over time to insure their relationship against fluctuations in lending conditions.

The first two papers look at the *extensive* margin of discretion in accept/reject decisions for consumer loans, we analyze the *intensive* margin for SME loans. The intensive margin may actually often be more relevant for firms once they have established a relationship with a particular bank. In our case the maximum exposure may deviate from the model limit as a result of the loan officer's discretion. We show that this type of discretion is important, and that there is both positive and negative discretion. More importantly, our set-up also allows us to control for any unobserved heterogeneity by looking at the changes in soft information and discretion over time, something which is typically not possible with accept/reject decisions only. Similar to their work though, we find that soft information partially explains the use of discretion and that discretion is more often used for collateralized loans. We also find that loans where discretion leads to different maximum exposures than those stemming from the bank's credit scoring model do not perform differently than loans based on the credit scoring model only. While Brown, Schaller, Westerfeld and Heusler (2012) show that discretion is primary used to insure bank relationships, we find in addition that loan officers use discretion to incorporate soft information in their lending decisions. This shows that repeated interactions enable lenders to incorporate soft information in lending decisions, as relationship lending theories argue (Sharpe, 1990; Rajan, 1992).

The remainder of this paper is organized as follows. Section 2 describes the data, the bank's lending and information collection process, our hardened soft information and discretion indicators. Section 3 describes the results. The final section concludes.

2. Data

In this section we document the data, the bank's monitoring process, and our empirical measures of soft information and discretion.

2.1 The Data

We use internal bank data come from the SME lending division of a multinational bank in Argentina. We have data since the foundation of this SME lending division in 1995 to 2001.[4] For each client the bank maintains a credit folder that contains all documents and forms employed by the loan officer since inception of the loan and during monitoring of the firm over the course of the lending relationship. We observe multiple monitoring cycles (i.e., credit revisions) for each firm over time since the inception of the bank-firm relationship.[5] We construct a panel data set of all evaluation points for all clients (640 firms) during the 7 year sample period.[6] In total we observe 2,501 evaluation points with on average 4 evaluation points per firm.

---

[4] The Argentinean financial crisis started in November 2001 at the end of our sample period and therefore does not affect our results.

[5] The SME lending division was founded in 1995 and "inherited" only 31 existing clients from other divisions in the bank. The other 95 percent of the clients we observe are therefore new to the bank since 1995.

[6] The firms have an average total asset size of 11.8 million dollars, an average return on assets of 7.4 percent and an average leverage ratio (i.e., debt to equity) of 2.12.

2.2 The Screening and Monitoring Process

The loan officer collects information about the firm at the inception of the lending relationship and at each credit revision. He visits the firm and talks with its owners, but also interacts with the firm's main customers and suppliers to collect information about the firm's creditworthiness. The standard customer evaluation form (0) is filled out and summarizes the collected data. This form typically contains 40 "measures" that summarize information about the firm's creditworthiness. Each variable has a minimum of 1 (bad) and a maximum of 4 (good). We use these measures to construct our indicators of soft, public and private hard information, which we discuss in the next subsection.

The loan officer could use discretion via two channels. Firstly, the loan officer could *upgrade* the model credit rating of the rating model if the loan officer beliefs that the firm has a better creditworthiness than the model credit rating. Second, the loan officer could use discretion by deviating from the model limit to set the maximum exposure of the bank to the firm.[7] The maximum exposure is determined in two steps. First, the credit scoring model employing public, private hard and soft information leads to a model limit. Second, the loan officer can either follow the model limit or employ his discretion to deviate from this model limit and set a different maximum exposure. Thus, the loan officer has the discretion to choose the model limit, or to positively or negatively deviate from the model limit.

Figure 2 shows a scatter plot of the model limit against the maximum exposure as determined by the loan officers. In 64 percent of the cases the loan officer follows the model limit (the 45 degree line), in 22 percent of the cases the loan officer uses "negative discretion" (i.e., the maximum exposure is lower than the model limit) and in 14 percent of the cases the loan officer uses "positive discretion" (i.e., the maximum exposure is larger than the model limit). We will show that the "discretion" exerted by loan officers is partly driven by their soft information. By deviating from the model limit, a loan officer is more likely to put his own reputation at risk. A loan officer can more easily be held accountable for this discretion as their supervisor easily can identify it and inquire why

---

[7] The maximum exposure is the maximum size of all short term, long term, covered and uncovered loans, trade credits and leases granted to the firm. The bank will never exceed this maximum exposure.

there was a deviation from the model limit. This risk of accountability is lower when the loan officer thinks highly about the firm, i.e., when he has favorable soft information. We use this unique feature of the data to test whether our measure of soft information explains loan officer discretion.

2.3 Measurement of Public, Private Hard and Soft Information

We study which type of information predicts default and determines lending outcomes. Table I presents the description of the public, private hard and soft information measures, the data sources and the summary statistics. Each variable has a minimum of 1 (bad) and a maximum of 4 (good) and the measure averages range from 2.25 to 3.99. Their standard deviations range from 0.00 to 1.36. The customer evaluation form employed by the bank differs across industries. While most measures are part of every form (e.g., whether a firm has previously been in a Chapter 11 procedure), some are industry specific (e.g., the fleet size of a transportation company).

Since we do no observe the same information measures for each credit evaluation we aggregate the individual information measures. To aggregate the measures, we divide the information collected in the customer evaluation form at the credit revisions into three types: public, private hard and soft information. We categorize information which is available to all potential lenders to a specific firm as "public". Examples are information from the credit registry and accounting data. We label information which is quantitative bank specific information as "private (hard)". Examples include the firm's repayment behavior on interest and principal, or information from the client's current and savings account.[8]

We use two criteria to identify "soft" information. The first criterion is that the information is collected through personal interaction with the borrower or its stakeholders. The second criterion is that human cognition is required to convert the

[8] Mester, Nakamura and Renault (2007) and Norden and Weber (2010) show that banks employ information about transaction account activity and credit line usage in their loan monitoring. This transaction information is quantitative, but only available internally in the bank. Therefore we classify this type of information as private hard information.

information into decision-relevant information.[9] To evaluate the first criterion, the bank documented the process how each variable was collected by a loan officer. For example, the bank explained that for the collection of the variable *Track Record with Main Suppliers* a loan officer would typically call suppliers to collect information about the firm's reputation and payment behavior of the trade credit.

To evaluate the second criterion we identify on the customer evaluation form (Figure 1) for which measures human cognition is required to enter the information. For some measures there are formal rules to translate information into an A to D score. For example, the debt-sales ratio gets a score of 'A' if this ratio is lower than 20 percent. However, other measures do not have such formal rules and are more subjective in nature. For example, the quality and reliance of information could be scored as 'strong', 'positive', 'neutral' or 'negative'. We identify measures without formal rule as measures which require human cognition. If the measure requires these two criteria – i.e, personal interaction and human cognition – we conclude that the measure is hardened soft information produced by the loan officer. Table I shows for each measure the source of the information, which could be the loan officer, internal bank data, accounting data of the firm or information from the central bank credit register. For each measure we also indicate whether human cognition is required to collect the measure.

Using the classification criteria describe above, we classify 13 measures as public information, 19 measures as private information and 8 measures as soft information measures. To aggregate these three information types we employ three methods to compute these aggregate indicators. The first is the equally weighted average of all measures for each information type labeled as "average information". The second employs the minimum score over all measures within an information type, labeled as "minimum". The third is a weighted average of all measures for each information type (we weigh each measure with its variance) labeled as "weighted information". The three aggregation methods are basically different weighting methods for the individual informations measures. The average information method puts an equal weight on each

[9] Agarwal and Hauswald (2010a) use the term 'subjective intelligence" to describe the subjective evaluation of the loan officer. This interpretation is close to our criterion that human cognition is required to process this information.

information measure, the minimum method puts all the weight on the measure with the minimum score and the weighted method puts more weight on measures with a high within firm standard deviation. The idea behind the last method is that information measures which vary more within the same firm contain more information about the changes in the actual creditworthiness of the firm.

Panel A of Table II presents the summary statistics of the aggregate information indicators. Since all information variables have a range from 1 (bad) to 4 (good) the mean values of the information indicators range from 2.45 to 3.71. Their standard deviations range from 0.34 to 1.11. The last column "sd within" shows that also soft information does not only vary across firms, but also *within* firms. Panel B presents the correlation coefficients between the public, private and soft information indicators. The correlation with the average soft indicator with the average public and private hard information is 0.21 and 0.08, respectively. These low correlations are surprising because a firm manager who is capable is expected to run his business and thus higher observable financial performance indicators. In the next section we will investigate in detail the potential explanations for this low correlation.

There are four explanations for this low correlation. The first explanation is that soft information substitutes public and private information when there is not sufficient public and private information available. We find that the number of soft information variables is negatively correlated with the number of private information variables and positively with the number of public information measures. This suggests that soft information could partly substitute a lack of private information, while more public information is also associated with more soft information. [10] Secondly, soft information could be uncorrelated with hard information contemporary, but predict hard information over time. To test this we estimate whether soft information collected in the previous period predict the levels and the changes in private and public information today. We find that past soft information predicts both changes in public information, but past public

[10] We estimate the number of soft information variables collected by the loan officer and report the results in Appendix II.

information predicts also change in soft information.[11] This suggests that soft and public information are both an independent and noisy signal about the creditworthiness of the firm and explains why they are uncorrelated. In section 0 we investigate in detail which of these signals is more precise and is better in predicting defaults. Third, part of the low correlation is mechanical. The information variables could take the value of 1 to 4, which coarsifies the information. This is the last reason for a low correlation.

Table II presents the summary statistics of the lending measures. The maximum exposure and the average model limit are slightly more than 1.2 million dollar. We rely on internal bank information for our loan delinquency indicator and employ three different measures of delinquency. The first measure is labeled *Default*. It takes the value of 1 in the first period that the firm repays the principal or interest rate late, and equals 0 otherwise. In the empirical analysis we exclude firms once they have defaulted. This reduces our sample to 1,756 observations of which 10 percent of the firms default on their loan. We use default as our primary delinquency measure. As alternative proxies of delinquency, we use *Loan Loss Provision,* the percentage of the maximum exposure on which a loan loss provision is made.

3. Empirical results

This section presents our empirical results. We first investigate whether soft information predicts loan defaults. Secondly, we examine whether soft information determines loan officers' discretion and evaluate the economic relevancy of soft information in the determination of the maximum exposure. Finally, we investigate whether loans with discretion perform differently than otherwise similar loans.

3.1 Does soft information help to predict loan default?

The collection of information by banks reduces the information asymmetry between the bank and the firm. Each piece of information collected is valuable to the bank if it

[11] We estimate whether the lags of the soft, private and public information indicators predict the current levels of the indicators and secondly whether the difference between the lagged information indicators predict the change in the information indicators. We report the results in Appendix III.

improves the predictability of lending outcomes, i.e., the loan delinquency. Therefore we firstly test whether information indicators of public, private hard and soft information predict loan delinquencies through the following specification:

$$\Pr(Delinquency_{it}) = \Phi(\beta_1 Soft_{it} + \beta_2 Pri_{it} + \beta_3 Pub_{it}), \quad (1)$$

where $Delinquency_{it}$ is *Default* or *Loan Loss Provision* of firm *i* at time *t*, Φ(.) is the standard normal cumulative distribution function, $Soft_{it}$ is the soft information indicator, Pri_{it} is the private hard information indicator, Pub_{it} is the public information indicator and X_{it} a matrix of control variables. We only include the firms in our sample which never defaulted before *t*.

Secondly we investigate whether changes in information indicators predict the delinquency indicators of the firm. We estimate the first difference of (2):

$$\Pr(Delinquency_{it}) = \Phi(\beta_1 \Delta Soft_{it} + \beta_2 \Delta Pri_{it} + \beta_3 \Delta Pub_{it} + \beta_3 \mathrm{X}_{it}) \qquad (2)$$

where $\Delta Delinquency_{it}$ *is* the first difference of our delinquency indicator (*Default*, or *Loan Loss Provision*), Φ(.) is the standard normal cumulative distribution function, $\Delta Soft_{it}$, ΔPri_{it}, and ΔPub_{it} are the lagged first differences of the soft, private hard and public information indicators, respectively. X_{it} is a matrix of control variables which includes time fixed effects and the first difference of the information set dummies.[12] In most specifications, we include firm size fixed effects, industry dummies, and loan officer fixed effects. The latter set of fixed effects should remove any idiosyncratic effects related to the behavior of a specific loan officer. We estimate equations (1) and (2) with Probit or OLS and cluster the standard errors at firm level. We report the marginal effects of the Probit estimations.

---

[12] Since we only include firms which never default before *t*, the delinquency measure in (2) is equal to the delinquency measure in (1).

Table III presents the results of the estimations of (1). We find a highly significant marginal effect of the soft information indicator. Model (1) for example shows that a one standard deviation worsening in the average soft information indicator from its mean increases the probability of default with 5.5 percentage points.[13] Public information also helps in predicting default: A one standard deviation decrease in public information increases the probability of default with 4 percentage points.[14] Average private hard information in contrast does not help in predicting default.[15] The loan officer collects the soft information and the quality of the soft information could reflect the ability of the loan officer. To test this we include loan officer fixed effects in Model (2) and show variation in soft information within the firms in the portfolio of one loan officer explains defaults. This suggests that the informational content of soft information and not the quality of the loan officer explains defaults. Model (4) employs the alternative measures of loan delinquency, loan loss provision. A one standard deviation decrease in soft information increases the loan loss provision with 5.5 percentage points.

Table IV presents the results of the estimation of specification (2) where we explain the change in default by lagged first differences of public, private hard and soft information. In this way we control for firm fixed effects and compare the impact of changes over time in information indicators for a given firm. We find that a one standard deviation decrease in the change in soft information for a given firm increases the probability of default with 3 percentage points. A one standard deviation decrease in our measure of public information also increases the probability of default with 3 percentage points. Thus, our previous results are not only driven by cross-sectional heterogeneity across firms but also by within-firm time-series variation: Changes in soft information for a given firm predict loan default and this with an equal magnitude as public information does. This suggests that soft information is an important source of information in the monitoring of a firm as it determines loan outcomes.

---

[13] The unconditional probability of default in this sub-sample is 10.0 percent.
[14] These findings are robust to taking the minimum or the weighted information indicators.
[15] We do find that individual private information which reflects the payment behaviour of the firm does predict defaults, which is consistent with Mester, Nakamura and Renault (2007) and Norden and Weber (2010).

3.2 Causality: Do Banks Cause or Predict Defaults?

The information collected by the bank could be helpful in predicting default. However, banks could also cause firms to default by setting loan terms that are not in line with the firm's repayment capacity and therefore trigger a firm's bankruptcy. We already partly deal with this concern by employing several loan delinquency indicators, in particular credit rating and loan loss provisions that in time come before any legal action of the bank and which therefore should not be driven by any legal action of the bank.

We further implement two strategies to address the causality concern. First, a borrower could default because the bank was over-lending such that the loan size and interest burden exceed the firm's repayment ability. Therefore we include the logarithm of the change in the maximum exposure in the previous period as a control variable.[16] The results in Model (5) of 0 and Model (5) of Table IV show that an increase in the maximum exposure in the previous monitoring cycle is negatively correlated with default. This reduces the concern that over-lending of banks pushes firms into default. Second, we run the regressions with the sub-sample of firms with multiple relationships as this reverse causality issue is less likely to play a role when the bank is only one of multiple lenders. The results of these regressions are reported in Model (6) of 0 and Model (6) of Table IV. Our result that soft information predicts loan delinquency still holds and if anything is even stronger.

3.3 Is Soft Information Used by Loan Officers?

In the previous section we show that soft information helps in predicting loan outcomes: Both the levels and first differences of soft information predict loan delinquencies. If soft information is valuable, do loan officers actually use information in their decisions on loan terms? In this subsection we study whether soft information explains loan officers' discretion.

---

[16] We first take the logarithm of the absolute change and then multiplied this with the sign of the change.

To test which information types explain discretion we estimate:[17]

$$Discretion_{it} = \beta_1 Soft_{it} + \beta_2 Pri_{it} + \beta_3 Pub_{it} + \beta_4 Model\ limit_{it} + \beta_4 X_{it} + \varepsilon_{it}, \quad (1)$$

Where $Discretion_{it}$ is the logarithm of the *Maximum exposure*$_{it}$ and the variables *positive discretion*$_{it}$ and *negative discretion*$_{it}$ which take the value of 1 if the *Maximum exposure*$_{it}$ is higher (lower) than the *Model limit*$_{it}$, *Soft*, *Pri*, *Pub* are our "average" information types and X_{it} is a matrix of other explanatory variables that determine discretion. The control variables include includes 6 year dummies, 3 firm sales size based dummies, 31 industry dummies and 21 regional dummies. We estimate equation (3) with OLS and Probit and cluster the standard errors at firm level.

Table V presents the results. We firstly estimate the total effect of soft information on the *Maximum exposure*$_{it}$. Column (1) shows that one standard deviation increase in soft information increases the maximum exposure with 20 percent, while a one standard deviation increase in public information increases the loan size with 15 percent. This shows that in addition to public information soft information has an economically significant impact on the maximum exposure of the bank to the firm. The bank uses the information variables to calculate a model credit rating. However, loan officers could use discretion to upgrade the model credit rating if they expect that the creditworthiness of the firm is better than the model's estimate. Column (2) shows that an *Upgrade* of the loan officer increases the maximum exposure of the firm with 33 percent. The effect of this form of loan officer discretion on the maximum exposure is significant. In the next section we analyze whether these upgrades are correlated with lower defaults to analyze whether this discretion is productive.

What is the impact of soft information on the decision of the loan officer to deviate from the model limit? To answer this question we add the model limit to the specification and present the results in column (3). The results show that soft information

[17] We exclude observations for which the model limit is zero. The model limit is zero when the firm has defaulted or is near default. Discretion then is driven by other factors such as the fact that the bank has an outstanding loan amount which cannot be recovered immediately.

continues to play an important role, even though some of the soft information partially determines the model limit. We also find that public information does not explain deviations from the model limit. The effect of the upgrades is not significant anymore because the credit rating after the upgrades is used to calculate the model limit.

An important finding in the literature on the impact of relationships on lending is that relationships increase the availability of credit (e.g. Petersen and Rajan, 1994). To assess the effect of relationships we include four relationship measures to the specification: *Inception, Relationship length, VIP* and *Outstanding*. The variable *Inception* measures whether the credit evaluation is the inception of the bank firm lending relationship, *Relationship length* measures the length of the lending relationship in years, *VIP* is a dummy variable which captures whether the bank identifies the firm as an important customer and could be interpreted as a measure of the scope of the relationship and *Outstanding* measures the actual outstanding exposure to the firm. We report the result in column (4) and show that loan officers set a higher exposure at the inception of the relationship and for important (*VIP*) customers. The length of the relationship does not affect the exposure to the firm.

The hierarchical structure of the bank might affect the use of discretion. We include three dummies which control for the approval level of the maximum exposure. We find that the approval level explain discretion but does not change the results. In addition we also include loan officer fixed effects and show that loan officer fixed effect explain discretion but does not affect the results.

Is there a difference between positive and negative discretion. To investigate this question we estimate the likelihood of positive and negative discretion. We show that relationship length does explains positive discretion and outstanding as predicted. A higher model limit negatively explains positive discretion. Negative discretion could be explained by soft information inception, VIP, Outstanding and the model limit.

3.4 Discretion and Loan Performance?

Soft information helps to predict loan delinquencies and loan officers partially employ soft information in their discretionary authority. The final question we are after is the role of discretion for loan delinquencies. In particular, we want to investigate whether loans granted with more discretion perform any differently than otherwise similar loans. We study two form of discretion: first the decision of the loan officer to upgrade the model credit rating and second the decision of the loan officer to deviate from the mode limit.

Table VI reports the results. In column (1) we include the model credit rating and the upgrade variable. A worse credit rating increases the probability of a delinquency, but in addition an upgrade decrease the probability of default with 3.4 percentage points. This suggests that loan officers use upgrades if the model gives the firm a too conservative credit rating. We showed the upgrade explain discretionary lending decisions and that these upgrades predict defaults. This suggests that the first form of discretion is productive. In column (2) we include the maximum exposure and the model limit. If the loan officer sets a high maximum exposure relative to the model limit, the likelihood of a delinquency increases, which suggests that discretion works counterproductive. However, if we include the relationship variables in column (3), the results shows that the outstanding credit amount of the firm drives this result. The loan officer is forced to use positive discretion if the firm has a higher outstanding credit amount than the model limit. When controlling for the outstanding amount we find that the second type of discretion is not related with the probability of a delinquency. We find similar results in column (4) when using the loan loss provision as dependent variable. The results suggest that the upgrades of the credit rating improve the predictability of the model, while deviations from the model limit are not correlated with the probability of a delinquency.

4. Conclusion

In this paper we address the question whether the collection of soft information and the use of discretion by loan officers generate value for the bank. We study whether loans based upon soft information and discretionary authority by loan officers has more favorable lending outcomes than otherwise similar loans. We construct direct measures of hardened soft information using the credit folders of a SME division of an international financial institution. We find that soft information predicts delinquencies in addition to public and private hard information.

We further find that soft information is not only valuable in predicting defaults, but is also actually used by loan officers. We analyze the observed deviations from the credit scoring model to test whether loan officers actually rely on soft information in wielding their discretionary authority. Soft information indeed partially explains discretionary authority while public and private hard information do not explain these deviations. The overall impact of a one deviation change of our measure of soft information results in a change of 16 percent of the maximum exposure of the firm. Finally, loans where the loan officer exerts discretion do not perform differently from otherwise similar loans.

Figure 1: Customer Evaluation Form

Loan officer use this form at the origination of the loan and at each credit revision. The loan officer collects the information about the firm and fills out the form to calculate the credit rating and model limit. We use this customer evaluation form to construct our information measures.

CUSTOMER SELECTION CRITERIA

SECTOR : Manufacturing **NAME:**

SEGMENT: **DATE:**

		A	B	C	D	Comments
	Primary Selection Criteria					
1	Previous Chapter 11	No	No	No	Yes	
2	Central Bank Classification (most recent)	1	1	1	2 or worse	
3	Years in Industry	>=7	>=5	>=3	<3	
4	Company & Personal Legal History	Strong	Positive	Neutral	Negative	
5	Company & Personal Checkings	Strong	Positive	Neutral	Negative	
6	Payment Behavior (Citibank)	A	B	C	D	
7	Composite Debt Index (*)	A	B	C	D	
	Secondary Customer Selection Criteria					Upgrades
8	Central Bank classification history (No "2" in last....)	>=24 months	>= 18 months	>= 12 months	< 12 months	
9	Interest Service Ratio	>= 3.0	>= 2.0	>= 1.0	< 1.0	
10	Total Debt / Sales	<= 20%	<= 35%	<= 50%	> 50%	
11	Overall Business Trend	A	B	C	D	
12	Profitability History (last 3 years)	3y pos.	2y pos. (incl. last)	2y pos.	<2y pos.	
13	Banking Debt with 1st. tier Banks	>=50%	>=30%	< 30%	N/A	
14	Encumbered Assets	None/Low	Medium	High	N/A	
15	Quality and Reliance of Information Provided	High	Medium	Basic	Unreliable	

(*) See table.

Preliminary Risk Grade
Secondary Risk Grade
Customer Risk Grade

Grade	Current Ratio	Leverage
Grade A	>= 1.2	<= 1.2
	>= 1.4	<= 2.0
Grade B	>= 1.0	<= 2.0
	>= 1.2	<= 3.0
Grade C	>= 0.8	<= 2.5
	>= 1.0	<= 4.0

APPROVALS:

Figure 2: Use of Discretion in Lending

Panel A displays a scatter plot of the lending decisions, where the model limit (i.e., the limit resulting from the credit scoring model) is plotted on the x-axis and the maximum exposure determined by the loan officer is plotted on the y-axis.

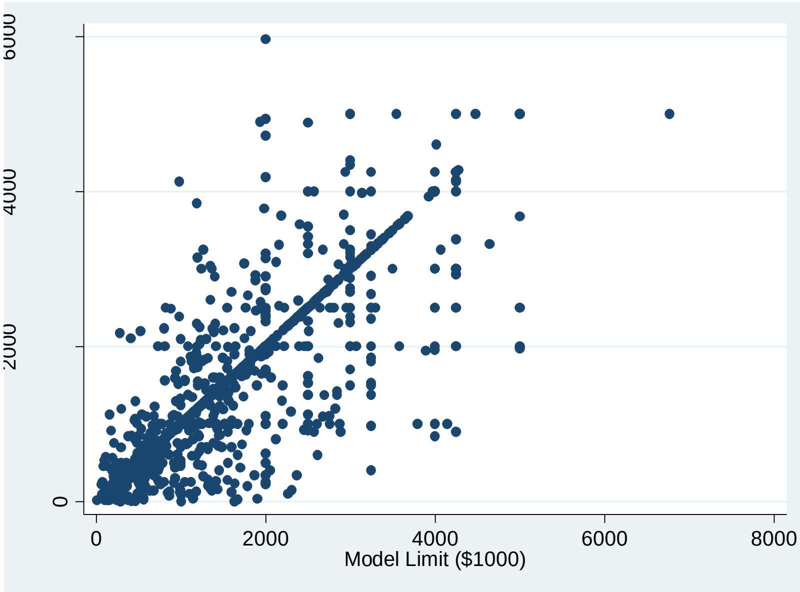


Table I: Information Variables

Table I presents the descriptive statistics of all the customer selections criteria. The customer selection criteria are divided in public information variables, private hard information, and soft information. *Source* gives the data source: Loan Officer (LO), Internal Bank Data (B), Accounting Data of the Firm (AC) or information from the Central Bank Credit Register (CB). Human cognition reports whether human cognition is required to collect the information. *Obs.*, *Mean*¸ *SD* and *Within SD* are the number of observations, the mean, standard deviation and standard deviation within a firm. The minimum and maximum of each measure is 1 (bad) and 4 (good).

The definitions of the bank specific variables are as follows: *Previous Chapter 11* describes whether the firm has been involved in a Chapter 11 procedure, *Central Bank Classification* is the most recent credit rating of the firm in the credit register, the *Composite Debt Index* is an index on the indebtedness of the firm, *Official Dealer* measures whether the firm is an official dealer, *Central Bank History Over Last 2 Years* measures the period since the last delinquency status in the credit registry and *Financial Status* is a measure of the financial health of the firm. *Payment Behavior* is the credit line usage and information from the transaction accounts of the borrower, *Encumbered Assets* are assets pledged as collateral and *Fleet Size* is the number of vehicles of transport companies. *Company and Personal Legal History* is the legal reputation of the firm and entrepreneur. The loan officer contacts suppliers and customers of the firm to collect this information. *Company Personal Checkings* is the judgment of the loan officer on the reputation and ability of the manager of the firm, based on the meetings with the manager. *Overall Business Trend* is the evaluation of the loan officer of the business plan and prospects of the firm, based on the meetings with the manager. *Trend in Sales* is the evaluation of the loan officer of the sales trend and prospects, based on the meetings with the manager. *Quality and Reliance of Information* is the evaluation of the loan officer of the quality of the information provided by the manager. *Track Record With Main Suppliers* is the reputation of the firm amongst the trade creditors of the firm. *Importance of Brand* is the evaluation of the loan officer of the relative importance of the brand name of the firm. *Customer Business and Relationships* is the reputation of the firm amongst its main business relationships and customers.

	Obs.	Source	Human cognition	Classification	Mean	SD.
Company and Personal Legal History	1,956	LO	Yes	Soft	3.79	0.53
Company Personal Checkings	1,932	LO	Yes	Soft	3.79	0.57
Overall Business Trend	262	LO	Yes	Soft	2.99	0.86
Trend in Sales	901	LO	Yes	Soft	3.16	0.96
Quality and Reliance of Information	1,893	LO	Yes	Soft	3.56	0.63
Track Record With Main Suppliers	392	LO	Yes	Soft	3.91	0.30
Importance of Brand	391	LO	Yes	Soft	3.91	0.34
Customer Business and Relationships	67	LO	Yes	Soft	3.42	0.70

Table I (continued)

	Obs.	Source	Human cognition	Classification	Mean	SD.
Payment Behavior	753	B		Private	3.76	0.58
Price Volatility Coverage	16	B		Private	2.88	1.36
Banking Debt With 1st Tier Banks	1,803	B		Private	3.89	0.44
Encumbered Assets	1,842	B		Private	3.59	0.68
Supplier Concentration	35	B		Private	3.40	0.91
Customer Concentration	34	B		Private	3.68	0.68
Years Relation With Main Customer	33	LO		Private	3.73	0.45
Percent Chattel Mortgaged	87	LO		Private	3.40	0.86
Average Age of the Fleet	94	LO		Private	3.37	0.73
Percent Owned Land	11	LO		Private	2.45	1.29
Percent Land Mortgaged	11	LO		Private	3.64	0.81
Fleet Size	18	LO		Private	4.00	0.00
ABF Transportation Occurrence	6	LO		Private	4.00	0.00
Percent Cash Sales	40	LO		Private	3.03	1.17
Facilities Ownership	40	LO		Private	2.95	1.13
Sales Breakdown	57	LO		Private	2.54	0.78
Monthly Sales By Vehicle	18	LO		Private	2.28	1.07
Sales / Square Meter	12	LO		Private	2.25	0.45
Insurance Company	20	LO		Private	3.70	0.73
Previous Chapter 11	1,969	CB		Public	3.99	0.17
Central Bank Classification	1,962	CB		Public	3.97	0.29
Years in Industry	1,979	LO		Public	3.82	0.50
Composite Debt Index	1,977	AC		Public	3.19	0.87
Official Dealer	169	LO		Public	3.99	0.08
Central Bank History Over Last 2 Years	1,952	CB		Public	3.81	0.64
Profitability History Last 3 Years	1,897	AC		Public	3.68	0.72
Dividend Pay-Out Ratio	894	AC		Public	3.13	1.21
Interest Service Ratio	1,929	AC		Public	3.48	1.00
Sales Turnover	328	AC		Public	3.11	0.96
Financial Debt Over Fixed Assets	9	AC		Public	2.67	1.32
Financial Status	40	AC		Public	2.85	0.86
Financial Debt/EBITDA	17	AC		Public	3.59	0.62

Table II: Summary Statistics

Table II presents the summary statistics of the aggregate information indicators (Panel A), the correlation coefficients (Panel B) and the summary statistics of the variables used in the empirical analysis (Panel C).

Panel A: Aggregate Public, Private Hard and Soft Information Indicators

We use three methods to aggregate the measures described in Appendix I. Firstly, we average the measures for each type (soft, private and public). Secondly, we take the minimum score for each type. Thirdly, we calculate the standard deviation of each measure and use the standard deviation to weight the measure in each information type. As sample we use all observations of the firms which never defaulted before time t, which results in a sample size of 1,756 firm observations.

	Aggregation Method	Obs.	Mean	SD.	Within SD.
Aggregate Indicators					
Soft Information	Average	1,756	3.69	0.35	0.21
	Minimum	1,756	3.12	0.85	0.56
	Weighted	1,756	3.65	0.38	0.24
Private Information	Average	1,756	3.72	0.41	0.27
	Minimum	1,756	3.39	0.84	0.54
	Weighted	1,756	3.55	0.67	0.35
Public Information	Average	1,756	3.70	0.28	0.16
	Minimum	1,756	2.53	1.08	0.66
	Weighted	1,756	3.58	0.41	0.24
Number of Information Variables					
Total number of information variables		1,756	14.12	1.82	1.10
Number of soft information variables		1,756	3.97	1.12	0.76
Number of private information variables		1,756	2.49	0.70	0.48
Number of public information variables		1,756	7.66	0.89	0.59

Panel B: Correlation Coefficients

	Average Private Information	Minimum Public Information
Average Soft Information	0.08	0.19
Average Private Information		0.11

Panel C: Summary statistics other variables

Panel C presents the summary statistics of the lending variables, the relationship characteristics and the delinquency indicators and provides the mean, median and standard deviation (SD) for all 1,756 firm observations. The definitions of the variables can be found in Appendix I.

Variable	Obs.	Mean	SD.	Min.	Max.
Lending variables					
Maximum Exposure ($1,000)	1,756	1215	1073	0	5961
Model Limit ($1,000)	1,756	1242	1121	0	6774
Positive Discretion	1,756	0.21	0.41	0	1
Negative Discretion	1,756	0.21	0.41	0	1
Model credit rating	1,756	2.86	0.95	1	4
Upgrade	1,756	0.33	0.47	0	1
Outstanding ($1,000)	1,756	358.3	606.1	0	4,998.77
Relationship variables					
Inception	1,756	0.34	0.47	0	1
Relationship Length (year)	1,756	2.57	2.43	0	32
VIP	1,756	0.06	0.24	0	1
Delinquency Indicators					
Default	1,756	0.10	0.30	0	1
Loan Loss Provisions	1,756	0.11	0.30	0	2.73

Table III: Soft Information and Loan Delinquencies

$$\Pr(Delinquency_{it}) = \Phi(\beta_1 Soft_{it} + \beta_2 Pri_{it} + \beta_3 Pub_{it})$$

Table III presents the results from regressions with the *Delinquency*$_{it}$ measures *Default*$_{it}$ or the *Loan Loss Provision*$_{it}$ as dependent variables. *Pub* $_{it-1}$, *Pri* $_{it-1}$, and *Soft* $_{it-1}$ are the public, hard private, and soft information indicator, respectively. In addition, the specification includes 6 year dummies, 3 firm sales size based dummies, 31 industry dummies, 21 regional dummies, 26 loan officer dummies and information set dummies (which are dummy variables for each information set in the customer evaluation form). In Model (5) we restrict the sample to include firms with multiple lending relationships, which decreases the sample size to 1,490 observations. We indicate the estimation method (Probit or OLS) and report robust standard errors clustered on a firm level. The marginal effect of the Probit models are reported in percentage points. Statistical significance at 10%, 5% and 1% levels is denoted by *, **, *** respectively .

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Default	Default	Loan Loss Provision	Default	Default
Model:	Probit	Probit	OLS	Probit	Probit
Soft $_{it}$	-0.08***	-0.07***	-0.08***	-0.08***	-0.06***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Pri $_{it}$	-0.01	-0.02	-0.01	-0.02	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Pub$_{it}$	-0.08***	-0.06***	-0.09***	-0.06***	-0.04**
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
Maximum exposure$_{it}$ / Total Assets$_{it}$				0.04	
				(0.05)	
Year, Firm Size, Industry, Regional and Information Set FE	Yes	Yes	Yes	Yes	Yes
Loan Officer FE		Yes	Yes	Yes	Yes
Obs.	1,756	1,756	1,756	1,756	1,490
(Pseudo) R-sq.	0.12	0.19	0.11	0.20	0.20

Table IV: Changes in Soft Information and Loan Delinquencies

$$\Pr(Delinquency_{it}) = \Phi(\beta_1 \Delta Soft_{it} + \beta_2 \Delta Pri_{it} + \beta_3 \Delta Pub_{it} + \beta_3 \mathrm{X}_{it})$$

Table IV presents the results from regressions with the $Delinquency_{it}$ measures $Default_{it}$ or the *Loan Loss* $Provision_{it}$ as dependent variables. $\Delta Soft_{it-1}$, ΔPri_{it-1}, ΔPub_{it-1}, are the first differences of the public information, private information and soft information indicator, respectively. In addition, the specification includes 6 year dummies and the information set dummies (which are dummy variables for each information set in the customer evaluation form). In Model (5) we restrict the sample to firms with multiple lending relationships. We indicate the estimation method (Probit or OLS) and report robust standard errors clustered on a firm level. The marginal effect of the Probit models are reported in percentage points. Statistical significance at 10%, 5% and 1% levels is denoted by *, **, *** respectively .

	(1)	(3)	(4)	(5)
Dependent variable:	Default	Loan Loss Provision	Default	Default
Model:	Probit	OLS	Probit	Probit
$\Delta Soft_{it}$	-0.08***	-0.07*	-0.08***	-0.09***
	(0.01)	(0.04)	(0.03)	(0.03)
ΔPri_{it}	-0.06***	-0.05*	-0.06***	-0.6**
	(0.02)	(0.03)	(0.03)	(0.02)
ΔPub_{it}	-0.08***	-0.14***	-0.07***	-0.09**
	(0.02)	(0.05)	(0.04)	(0.04)
$Soft_{it-1}$	-0.09***	-0.07*	-0.08***	-0.10***
	(0.01)	(0.04)	(0.03)	(0.03)
Pri_{it-1}	-0.02	-0.03	-0.02	-0.02
	(0.02)	(0.03)	(0.02)	(0.03)
Pub_{it-1}	-0.02	-0.10**	-0.02	-0.02
	(0.03)	(0.04)	(0.03)	(0.04)
Maximum exposure / Total $Assets_{it}$			-0.09	
			(0.08)	
Year, Firm Size, Industry, Regional, Information Set FE.	Yes	Yes	Yes	Yes
Obs.	1,141	1,141	1,141	1,000
(Pseudo) R-sq.	0.13	0.09	0.13	0.13

Table V: How Do Loan Officers Use Discretion?

$$Discretion_{it} = \beta_1 Soft_{it} + \beta_2 Pri_{it} + \beta_3 Pub_{it} + \beta_4 Model\ limit_{it} + \varepsilon_{it}$$

Table V presents the results from regressions with the *Ln Maximum Exposure*$_{it}$ (Max Exp) as dependent variable in columns (1)-(6), *positive discretion*$_{it}$ in column (7) and *negative discretion*$_{it}$ in column (8). The definitions of the independent variables can be found in Appendix I. In addition, the specification includes 6 year dummies, 3 firm sales size based dummies, 31 industry dummies, 21 regional dummies, 26 loan officer dummies and information set dummies (which are dummy variables for each information set in the customer evaluation form). We estimate the regression with Probit and OLS and report robust standard errors clustered on a firm level. The marginal effect of the Probit models are reported in percentage points. Statistical significance at 10%, 5% and 1% levels is denoted by *, **, *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Max Exp	Max Exp	Max Exp	Max Exp	Max Exp	Max Exp	Positive	Negative
Model:	OLS	OLS	OLS	OLS	OLS	OLS	Probit	Probit
$Soft_{it}$	0.58***	0.58***	0.40***	0.37***	0.29***	0.30***	2.14	-8.04***
	(0.12)	(0.12)	(0.11)	(0.11)	(0.10)	(0.10)	(3.37)	(2.70)
Pri_{it}	0.11	0.15	0.06	0.03	-0.01	-0.05	-7.73**	2.70
	(0.12)	(0.10)	(0.09)	(0.08)	(0.08)	(0.08)	(3.01)	(2.64)
Pub_{it}	0.55***	0.66***	-0.21	-0.04	0.01	0.05	-8.95*	-8.24**
	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)	(0.12)	(5.05)	(4.21)
$Upgrade_{it}$		0.33***	-0.02	-0.04	-0.04	-0.09	-6.15**	-0.44
		(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.02)	(0.21)
$Inception_{it}$				0.30***	0.28***	0.26***	-2.51	-9.39***
				(0.09)	(0.08)	(0.08)	(2.90)	(2.03)
Ln Relationship $Length_{it}$				0.04	-0.03	-0.01	15.10***	2.82
				(0.13)	(0.13)	(0.13)	(4.90)	(3.20)
VIP_{it}				0.44***	0.26***	0.26***	-0.54	-8.32**
				(0.08)	(0.08)	(0.08)	(4.58)	(2.37)
$Outstanding_{it}$				0.08***	0.07***	0.07***	1.27***	-0.90***
				(0.01)	(0.01)	(0.01)	(0.38)	(0.20)
Ln Model $Limit_{it}$			0.24***	0.23***	0.23***	0.22***	-9.37***	10.32***
			(0.03)	(0.03)	(0.03)	(0.03)	(0.97)	(1.12)
Year, Firm Size, Industry, Regional and Information Set FE	Yes		Yes	Yes	Yes	Yes	Yes	Yes
Approval Level FE					Yes	Yes	Yes	Yes
Loan Officer FE						Yes	Yes	Yes
Obs.	1,756	1,756	1,756	1,756	1,756	1,756		
Adj. R-sq	0.30	0.31	0.36	0.39	0.47	0.49	0.42	0.24

Table VI: Discretion and Loan Delinquency

$$\Pr(Delinquency_{it}) = \Phi(\beta_1 Discretion_{it} + \beta_3 X_{it})$$

Table VI presents the results from regressions with the *Delinquency$_{it}$* measures *Default$_{it}$* or the *Loan Loss Provision$_{it}$* as dependent variables. $\Delta Soft_{it-1}$, ΔPri_{it-1}, ΔPub_{it-1}, are the first differences of the public information, private information and soft information indicator, respectively. In addition, the specification includes 6 year dummies and the information set dummies (which are dummy variables for each information set in the customer evaluation form). We indicate the estimation method (Probit or OLS) and report robust standard errors clustered on a firm level. The marginal effect of the Probit models are reported in percentage points. Statistical significance at 10%, 5% and 1% levels is denoted by *, **, *** respectively .

	(1)	(2)	(3)	(4)
Dependent variable	Default	Default	Default	Loan Loss Provision
Estimation	Probit	Probit	Probit	OLS
Model rating $_{it}$	4.80***	5.35***	4.05***	0.04***
	(0.90)	(1.06)	(0.99)	(0.01)
Upgrade$_{it}$	-3.35**	-4.07***	-3.16**	-0.06***
	(0.02)	(1.71)	(1.47)	(0.023)
Maximum exposure$_{it}$		1.90***	0.35	0.005
		(0.56)	(0.55)	(0.004)
Model Limit$_{it}$		-0.11	0.13	0.00
		(0.41)	(0.35)	(0.00)
Inception$_{it}$			-0.61	-0.015
			(1.52)	(0.022)
Ln Relationship Length$_{it}$			-8.76***	-0.098***
			(3.00)	(0.024)
VIP$_{it}$			0.74	-0.035
			(2.39)	(0.032)
Outstanding$_{it}$			1.69***	0.014***
			(0.28)	(0.002)
Year and Information Set FE.	Yes	Yes	Yes	Yes
Obs.	1,133	1,133	1,133	1,133
(Pseudo) R-sq.	0.12	0.13	0.18	0.09

Appendix I: Variable definitions

Variable name	Definition
Average Soft Information (Soft)	Average score of the soft information variables identified in Table I.
Average Private Information (Pri)	Average score of the private information variables identified in Table I.
Average Public Information (Pub)	Average score of the public information variables identified in Table I.
Total number of information variables	Total number of information variables filled out on the customer selection criteria form.
Number of soft information variables	Number of soft information variables filled out on the customer selection criteria form.
Number of private information variables	Number of private information variables filled out on the customer selection criteria form.
Number of public information variables	Number of public information variables filled out on the customer selection criteria form.
Maximum Exposure ($1,000)	The maximum exposure to the firm determined by the loan officer at each credit decision. The maximum exposure is the maximum sum of credit lines, term loans and financial leases to the firm.
Model Limit ($1,000)	The result of the bank's internal model.
Positive Discretion	= 1 if Maximum Exposure > Model Limit and 0 otherwise.
Negative Discretion	= 1 if Maximum Exposure < Model Limit and 0 otherwise.
Model credit rating	The minimum score of all the information variables on the customer selection criteria form.
Upgrade	= 1 if the loan officer upgraded the model credit rating to a higher credit score and 0 otherwise.
Outstanding ($1,000)	The amount of outstanding loans to the firm.
Inception	= 1 if the credit evaluation is the first evaluation of the firm.
Relationship Length (year)	Length of the lending relationship between the bank and the firm.
VIP	= 1 if the firm is an important customer for the bank.
Default	= 1 if the firm defaults within a period of one year.
Loan Loss Provisions	The share of loan loss provisions of the maximum exposure.

Appendix II: Collection of Soft Information

$$Number\ of\ soft\ information\ variables_{it} = \beta_1 Relationship_{it} + \beta_2 X_{it} + \varepsilon_{it}$$

Appendix II presents the results from regressions with the $Number\ of\ soft\ information\ variables_{it}$ as dependent variable. The definitions of the independent variables can be found in Appendix I. In addition, the specification includes 6 year dummies, 3 firm sales size based dummies, 31 industry dummies, 21 regional dummies and 26 loan officer dummies. All specifications are estimated with OLS. Statistical significance at 10%, 5% and 1% levels is denoted by *, **, *** respectively . Standard errors are robust and clustered at the firm level.

	(1)	(2)	(3)	(4)
Relationship length	0.004	0.004	0.004	0.01*
	(0.008)	(0.008)	(0.008)	(0.006)
Inception	0.051	0.051	0.081*	0.029
	(0.041)	(0.041)	(0.043)	(0.033)
Number of private information variables				-0.05*
				(0.02)
Number of public information variables				0.86***
				(0.03)
Year, Firm Size, Industry and Regional FE	Yes	Yes	Yes	Yes
Approval Level FE		Yes	Yes	Yes
Loan Officer FE			Yes	Yes
Obs.	1,756	1,756	1,756	1,756
Adj. R-sq	0.62	0.62	0.63	0.78

Appendix III: Correlation of Information over Time

$$Information\ indicator_{it} = \beta_1 Soft_{it-1} + \beta_2 Pri_{it-1} + \beta_3 Pub_{it-1} + \varepsilon_{it}$$

Appendix III presents the results from regressions with the $Information\ indicator_{it}$ as dependent variable. The information indicators are the levels of the average soft, private and public indicators in columns (1)-(3) respectively and the first differences of the average soft, private and public indicators in columns (4)-(5) respectively. The definitions of the independent variables can be found in Appendix I. In addition, the specification includes 6 year dummies, 3 firm sales size based dummies, 31 industry dummies, 21 regional dummies, 26 loan officer dummies. The sample reduces to 1,133 because of the exclusion of the first observation of each firm. All specifications are estimated with OLS. Statistical significance at 10%, 5% and 1% levels is denoted by *, **, *** respectively . Standard errors are robust and clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	$Soft_{it}$	Pri_{it}	Pub_{it}	$\Delta Soft_{it}$	ΔPri_{it}	ΔPub_{it}
$Soft_{it-1}$	0.47^{***}	-0.04	0.05^{**}			
	(0.03)	(0.03)	(0.02)			
Pri_{it-1}	-0.03	0.39^{***}	0.02			
	(0.02)	(0.04)	(0.02)			
Pub_{it-1}	0.10^{***}	-0.03	0.61^{***}			
	(0.04)	(0.04)	(0.04)			
Pri_{it-1}- $Soft_{it-1}$				0.05^{**}	-0.19^{**}	
				(0.02)	(0.03)	
Pub_{it-1} - $Soft_{it-1}$				0.31^{***}		0.16^{***}
				(0.03)		(0.02)
Pub_{it-1} - Pri_{it-1}					0.30^{***}	-0.07^{***}
					(0.04)	(0.02)
Year, Firm Size, Industry, Regional, Loan Officer FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,133	1,133	1,133	1,133	1,133	1,133
R-sq	0.413	0.387	0.433	0.277	0.328	0.042

Bibliography

Agarwal, S., and I. Ben-David, 2012, Do Loan Officers' Incentives Lead to Lax Lending Standards?, Working Paper.

Agarwal, S., and R. Hauswald, 2010a, Authority and Information, Working Paper.

Agarwal, S., and R. Hauswald, 2010b, Distance and Private Information in Lending, *Review of Financial Studies* 23, 2757-2788.

Akhavein, J., W. S. Frame, and L. White, 2005, The Diffusion of Financial Innovations: an Examination of the Adoption of Small Business Credit Scoring by Large Banking Organizations, *Journal of Business* 78, 577-596.

Almeida, H., and M. Campello, 2007, Financial Constraints, Asset Tangibility, and Corporate Investment, *Review of Financial Studies* 20, 1429-1460.

Asquith, P., R. Gertner, and D. Scharfstein, 1994. Anatomy of Financial Distress: an Examination of Junk-Bond Issuers, *Quarterly Journal of Economics* 109, 625–658.

Ayres, I. and P. Siegelman, 1995, Race and Gender Discrimination in Bargaining for a New Car, *American Economic Review* 85, 304-321.

Beck, T., and A. Demirgüç-Kunt, 2009, Financial Institutions and Markets Across Countries and over Time: Data and Analysis, Working Paper.

Berg, T., M. Puri, and J. Rocholl, 2013, Loan Officer Incentives and the Limits of Hard Information, Working Paper.

Berger, A. N., and G. F. Udell, 1995, Small Firms, Commercial Lines of Credit, and Collateral, *Journal of Business* 68, 351-382.

Berger, A. N., S. Frame and V. Ioannidou, 2011, Tests of Ex Ante versus Ex Post Theories of Collateral using Private and Public Information, *Journal of Financial Economics* 100, 85-97.

Benmelech, E., and N. Bergman, 2008. Liquidation Values and the Credibility of Financial Contract Renegotiation: Evidence from U.S. Airlines, *Quarterly Journal of Economics* 123, 1635–1677.

Bester, H., 1985, Screening versus Rationing in Credit Markets with Imperfect Information, *American Economic Review* 75, 850-855.

Berg, T., M. Puri, and J. Rocholl, 2013, Loan Officer Incentives and the Limits of Hard Information, Working Paper.

Berger, A. N., N. H. Miller, M. A. Petersen, R. G. Rajan, and J. C. Stein, 2005, Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks, *Journal of Financial Economics* 76, 237-269.

Bertrand, M., E. Duflo, and S. Mullainathan, 2004, How Much Should We Trust Difference-In-Difference Estimates?, *Quarterly Journal of Economics* 119, 249-275.

Bharath, S. T., S. Dahiya, A. Saunders and A. Srinivasan, 2011, Lending Relationships and Loan Contract Terms, *Review of Financial Studies* 24, 1141-1203.

Boot, A, 2000, Relationship Banking. What Do We Know? *Journal of Financial Intermediation* 9, 7–25.

Boot, A., and A. Thakor, 1994, Moral Hazard and Secured Lending in an Infinitely Repeated Credit Market Game, *International Economic Review* 35,899–920.

Brown, M., M. Schaller, S. Westerfeld, and M. Heusler, 2012, Information or Insurance, On the Role of Loan Officer Discretion in Credit Assessment, Working Paper.

Cerqueiro G., H. Degryse, and S. Ongena, 2011, Rules versus Discretion in Loan Rate Setting, *Journal of Financial Intermediation* 20, 503-529.

Cerqueiro, G., K. Roszbach, and S. Ongena (*forthcoming*), Collateralization, bank loan rates and monitoring, *Journal of Finance*.

Chakraborty, C. X. Hu, 2006, Lending Relationships in Line-of-Credit and Nonline-of-Credit Loans: Evidence from Collateral Use in Small Business, *Journal of Financial Intermediation* 15, 86–107.

Chatterjee, K., and C. C. Lee, 1998, Bargaining and Search with Incomplete Information about Outside Options, *Games and Economic Behavior* 22, 203-237.

Collins, N., 1966, Credit Analysis – Concepts and Objectives, in: Baughn, W.H., and C.E. Walker (Eds.), *The Banker's Handbook*, 279-289.

Crawford, V. P., and J. Sobel, 1982, Strategic Information Transmission, *Econometrica* 50, 1431-1451.

Degryse, H., and S. Ongena, 2005, Distance, Lending Relationships, and Competition, *Journal of Finance* 60, 231-266.

Degryse, H., M. Kim, and S. Ongena, 2009, *Microeconometrics of Banking. Methods, Applications, and Results*, Oxford University Press.

Degryse, H., and P. Van Cayseele, 2000, Relationship Lending within a Bank-Based System: Evidence from European Small Business Data, *Journal of Financial Intermediation* 9, 90-109.

Dessein, W., 2002, Authority and Communication in Organizations, *Review of Economic Studies* 69, 811-838.

Diamond, D. W., 1984, Financial Intermediation and Delegated Monitoring, *Review of Economic Studies* 51, 393-414.

Duffie, D., N. Gârleanu, and L. H. Pedersen, 2005, Over-the-Counter Markets, *Econometrica* 73, 1815-1847.

Duffie, D., N. Gârleanu, and L. H. Pedersen, 2007, Valuation in Over-the-Counter Markets, *Review of Financial Studies* 20, 1865-1900.

DNB, 2012, Bank Lending Survey: Banks are Expecting Decline in Demand, http://www.dnb.nl/en/news/news-and-archive/statistisch-nieuws-2012/dnb267623.jsp.

Fried, J., and P. Howitt, 1980, Credit Rationing and Implicit Contract Theory, *Journal of Money, Credit, and Banking* 12, 471-487.

Gilson, S., 1990, Bankruptcy, Boards, Banks, and Blockholders: Evidence on Changes in Corporate Ownership and Control when Firms Default, *Journal of Financial Economics* 26, 315–353.

Gilson, S., K. John, and L. Kang, 1990, Troubled Debt Restructurings: An Empirical Analysis of Private Reorganization of Firms in Default. *Journal of Financial Economics* 26, 315–353.

Green, C. H., 1999, *The SBA Loan Book*, Adams Media, MA.

Gropp, R., C. Gruendl, and A. Guettler, 2013, Hidden Gems and Borrowers with Dirty Little Secrets. Investment in Soft Information, Borrower Self-Selection and Competition, Working Paper.

Grunert, J., and L. Norden, 2012, Bargaining Power and Information in SME Lending, *Small Business Economics* 39, 401-417.

Hadlock, C. J., and J. R. Pierce, 2010, New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index, *Review of Financial Studies* 23, 1909-1940.

Harris, M., and A. Raviv, 2005, Allocation of Decision-Making Authority, *Review of Finance* 9, 353–383.

Heider, F., and R. Inderst, 2012, Loan Prospecting, *Review of Financial Studies* 25, 2381–2415.

Hertzberg, A., J. M. Liberti, and D. Paravisini, 2010, Information and Incentives Inside the Firm. Evidence from Loan Officer Rotation, *Journal of Finance* 65, 795-828.

Hofstede, G., 1991, *Cultures and Organizations. Software of the mind*, New York, McGraw-Hill.

Holmstrom, B, and J. Tirole, 1997, Financial Intermediation, Loanable Funds, and the Real Sector, *The Quarterly Journal of Economics* 112, 663-691.

Inderst, R., and H. M. Müller, 2004, The Effect of Capital Market Characteristics on the Value of Start-Up Firms, *Journal of Financial Economics* 72, 319–356.

Ioannidou, V., and S. Ongena, 2010, Time for a Change: Loan Conditions and Bank Behavior when Firms Switch Banks, *Journal of Finance* 55, 1847-1876.

Lee, C. C., 1994, Bargaining and Search with Recall. A Two-Period Model with Complete Information, *Operational Research* 42, 1100-1109.

Liberti, J. M., 2005, Initiative, Incentives and Soft Information. How Does Delegation Impact the Role of Bank Relationship Managers?, Working Paper.

Liberti, J. M., and A. R. Mian, 2009, Estimating the Effect of Hierarchies on Information Use, *Review of Financial Studies* 22, 4057-4090.

Liberti, J. M., A. Seru, and V. Vig, 2012, Information, Credit and Organization, Working Paper.

Mach, T. L., and J. D. Wolken, 2006, Financial Services Used by Small Businesses: Evidence from the 2003 Survey of Small Business Finances, *Federal Reserve Bulletin* 167-195.

Marino, A. M., and J. G. Matsusaka, 2005, Decision Processes, Agency Problems, and Information. An Economic Analysis of Capital Budgeting Procedures, *Review of Financial Studies* 18, 301-325.

Mertens, L., 2014, Engum flýgur sofanda steikt gæs i munn.

Mester, L. J., L. Nakamura, and M. Renault, 2007, Transaction Accounts and Loan Monitoring, *Review of Financial Studies* 20, 529-556.

Morton , F.S., F. Zettelmeyer, and J. Silva-Risso, 2004, A Test of Bargaining Theory in the Auto Retailing Industry, Working Paper.

Norden, L., and M. Weber, 2010, Credit Line Usage, Checking Account Activity, and Default Risk of Bank Borrowers, *Review of Financial Studies* 23, 3665-3699.

Petersen, M. A., 2004, Information: Hard and Soft, Working Paper.

Petersen, M. A., and R. G. Rajan, 1994, The Benefits of Lending Relationships. Evidence from Small Business Data, *Journal of Finance* 49, 3-37.

Petersen, M. A., and R. G. Rajan, 1995, The Effect of Credit Market Competition on Firm-Creditor Relationships, *Quarterly Journal of Economics* 110, 407-443.

Puri, M., J. Rocholl, and S. Steffen, 2011, Rules versus Discretion in Bank Lending Decisions, Working Paper.

Qian, J., P. E. Strahan, and Z. Yang, 2012, The Impact of Incentives and Communication Costs on Information Production. Evidence from Bank Lending, Working Paper.

Rajan, R. G., 1992, Insiders and Outsiders: The Choice between Informed and Arm's-Length Debt, *Journal of Finance* 47, 1367-1400.

Roth, A. E., V. Prasnikar, M. Okuno-Fujiwara, and S. Zamir, 1991, Bargaining and Market Behavior in Jerusalem, Ljubljana, Pittsburh, and Tokyo. An Experimental Study, *American Economic Review* 81, 1068-1095.

Roberts, M. R., and A. Sufi, 2009, Renegotiation of Financial Contracts: Evidence from Private Credit Agreements, *Journal of Financial Economics* 93, 159–184.

Rubinstein, A., and A. Wolinsky, 1985, Equilibrium in a Market with Sequential Bargaining, *Econometrica* 53, 1133-1150.

Santikian, L., 2012, The Ties that Bind: Bank Relationships and Small Business Lending, Forthcoming *Journal of Financial Intermediation.*

Santos, J. A. C., and A. Winton, 2008, Bank Loans, Bonds, and Information Monopolies Across the Business Cycle, *Journal of Finance* 63, 1315-1359.

Sharpe, S. A., 1990, Asymmetric Information, Bank Lending and Implicit Contracts: A Stylized Model of Customer Relationships, *Journal of Finance* 45, 1069–1087.

Shavell, S., 2007, On the Optimal Discretion in the Application of Rules, *American Law and Economics Review* 9, 175-194.

Stein, J. C., 2002, Information Production and Capital Allocation: Decentralized versus Hierarchical Firms, *Journal of Finance* 57, 1891-1921.

Stigler, G. J, 1961, The Economics of Information, *Journal of Political Economy*, 69, 213-225.

Tirole, J., 2006, *The Theory of Corporate Finance*, Princeton University Press.

Von Thadden, E., Asymmetric Information, Bank Lending and Implicit Contracts, The Winner's Curse, *Finance Research Letters* 1, 11-23.